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PERFORMANCE OF DIA AND FORWARD-LOOKING OPTIMAL PORTFOLIOS OF DOW STOCKS

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ABSTRACT

Purpose- This paper compares the performance of DIA, trailing optimal portfolio and forward-looking optimal portfolio constructed from a pool of DOW stocks, applying a modified contrarian portfolio construction to the forward-looking optimization. The modified contrarian optimization of this study is based on the premise that loser stocks, in the short run, would have reversal performance and become winner stocks in the short-run future. The investigative question is: Do forward-looking optimal portfolios of DOW stocks perform better than trailing optimal portfolios of DOW stocks in the short run after DJIA hit the year's lowest point in 2022?
Methodology- To answer the investigative question, this study compares the short-run performance of forward-looking optimal portfolios with the performance of trailing optimal portfolios. Elton, Gruber, and Padberg (1987) originally introduced the optimal portfolio technique.
Findings- The primary focus was on the case related to September 30, 2022, when DJIA hit the lowest level in 2022. To get the trend analysis of the cases of DJIA hitting the lowest level of the year, this study examined two comparable findings, having examined the performance properties of trailing vs. forward-looking optimal portfolios using the same method. One examined the case related to March 23, 2020, and another examined the case related to December 24, 2018. It finds a robust performance of DIA compared to the performance of two forms of optimal portfolios. It also finds that forward-looking optimal portfolios performed better than trailing optimal portfolios regarding the average performance of three cases.
Conclusion- It concludes the potential usefulness of DIA as evidence of the market efficiency of DOW stocks. At the same time, forward-looking optimal portfolios for short-run investment in DOW stocks are a viable alternative to investing in the DIA.

Keywords: Portfolio choice, portfolio optimization, event studies, DIA, DOW stocks
JEL Codes: G11, G14, G17

1. INTRODUCTION

This study examines the portfolio performance of DOW stocks and DIA (SPDR Dow Jones Industrial Average ETF) as a proxy of the Dow Jones Industrial Average (DJIA) Index after the event date of September 30, 2022, when DJIA hit its lowest point of 2022. In this study, “winners” mean top-half component performers beating DIA (i.e., performance ranks 1 through 13), and “losers” mean bottom-half performers not beating DIA (i.e., performance ranks 14 through 30) during the first half of the sample period. The reason for including the rank 14th stock in the loser group is that the DIA happens to be the rank 14 in this study if DIA were included in the ranking, so when ranking only 30 index components, the loser stocks mean the components underperforming DIA, the DJIA proxy. It analyzes the performance of the conventional, backward-looking (trailing) optimal portfolio constructed from the pool of 30 Dow stocks, using the daily data sample period from July 27, 2022, to September 30, 2022. As an alternative, it also analyzes the performance of the forward-looking optimal portfolio, using the same sample period, based on a contrarian premise, constructed from the pool of 17 loser-DOW stocks during the first half of the sample period.

This paper is organized as follows: the next section explains forward optimal portfolios; the second section is a literature review; the third section describes the investigative design and methodology; the fourth section explains the findings, the concluding section sets forth a conclusion and further study. Four figures with corresponding tables presenting this study's critical descriptive and analytical statistics are placed in the findings section. The references section is placed last.

2. FORWARD OPTIMAL PORTFOLIOS EXPLAINED

The premise of contrarian investing is that investing the same way everyone else thinks leads to wrong investing. That is, it is contrary to the herd instinct. In a way, contrarian investing is consistent with value investing in that the contrarian invests in mispriced investments that are undervalued by the market. An early pioneer of implementing a contrarian premise in active portfolio investment was Economist John Maynard Keynes (Chambers & Dimson, 2013). For example, Keynes was an early contrarian investor when he managed the endowment for King's College, Cambridge, from the 1920s to '40s in the sense that while most endowments invested primarily on land and fixed-income securities, Keynes invested heavily in common stocks and outperformed the UK stock market. French and Dreman Value Management (2010) have advocated contrarian investing, focusing on low P/E ratio stocks. In the classic study, Dreman demonstrates that Low-P/E stocks have outperformed the S&P 500 and high-P/E stocks in the last five decades (1960s ~2000s).

Applying the premise of value investing or contrarian investing, this study constructs contrarian portfolio optimization based only on the pool of loser-Dow stocks. This proxy contrarian optimal portfolio construction is referred to as "forward-looking portfolio optimization," which is the operational definition in this study. It is contrary to conventional or trailing portfolio optimization, which is based only on the historical properties of components of the portfolio pool.

3. LITERATURE REVIEW

The weakness of the trailing optimal portfolio construction is that it favors high-performance stocks in terms of the return per unit of risk among the components of the portfolio pool based on historical data. As evidenced by this study, the conventional optimal portfolio failed to capture any high-performance stocks in the second half of the sample period. The conventional optimal portfolio construction based on past performance does not guarantee comparable results in the short-run future. Thus, the empirical evidence of this study on the trailing optimal portfolio supports the notion of SEC Rule 156 (2024), which says, "It is unlawful for any person, directly or indirectly, by the use of any means or instrumentality of interstate commerce or of the mails, to use sales literature which is materially misleading in connection with the offer or sale of securities issued by an investment company …" This is why the SEC (2024) requires funds to tell investors that "a fund's past performance does not necessarily predict future results." Providing evidence for the SEC requirement, Blake, Elton, and Gruber (1993) showed that, on average, bond funds underperform passive fixed-income indexes by an amount roughly equal to expenses and that there is no evidence that past performance can predict future performance.

Markowitz (1952) states, "The process of selecting a portfolio may be divided into two stages. The first stage starts with observation and experience and ends with beliefs about the future performances of available securities. The second stage starts with the relevant beliefs about future performances and ends with the portfolio choice." Markowitz proposed an alternative rule: Investors should consider expected return desirable and variance of return undesirable. This rule emphasizes the trade-off between risk (variance) and reward (expected return). In Markowitz's second stage, this paper expects the potentially inferior performance of the trailing optimal portfolio in terms of return per unit of risk, so it explores a forward-looking optimal portfolio proxy of DOW stocks constructed from the pool of 17 losers of DOW stocks during the first sub-sample period. Then, it compares the performance of the forward-looking optimal portfolio with the performance of the trailing optimal portfolios of DOW stocks during the second sub-sample period for back-testing. This paper also explores a similar comparison with DIA, the DJIA index proxy for the same subperiods, to examine the degree of market efficiency during the worst day, September 30 of the year 2022 event.

The Efficient Market Hypothesis (EMH) suggests that security prices fully reflect all relevant information, making it impossible to beat the market consistently. Practical evidence of this EMH is that passively invested in a market index fund like DIA outperforms managed portfolios such as optimal portfolios presented in this paper. For example, Johnson (2021) reports that "In general, actively managed funds have failed to survive and beat their benchmarks, especially over longer time horizons; only 25% of all active funds topped the average of their passive rivals over the ten years ended June 2021; long-term success rates were generally higher among foreign-stock, real estate, and bond funds and lowest among U.S. large-cap funds. The S&P Indices versus Active (SPIVA) scorecard, which tracks the performance of actively managed funds against their respective category benchmarks, recently showed that 79% of fund managers underperformed the S&P last year. It reflects an 86% jump over the past ten years."

The inferior performance of the trailing optimal portfolio would be a practical issue despite the theoretical breakthrough of Markowitz's mean-variance portfolio optimization (Markowitz, 1952). The practical issue is that past performance is no guarantee for future performance, as explained in the previous paragraph. For example, Bielstein and Hanauer (2017) suggest using the ICC (Implied Cost of Capital) based on analysts' earnings forecasts as a forward-looking return estimate to overcome such a practical issue. Another possibility is, as suggested by Jagannathan and Ma (2003), to focus on the minimum variance portfolio (MVP) construction, which would mitigate the estimation errors. However, deriving the ultimate optimal portfolio from the MVP construction could be even more challenging. If the forward-looking optimal portfolio proxy in this study is utilized effectively, it could capture the winners of the second half of the sample period of this study. Such forward-looking optimal portfolio construction would aim to capture winners in the second sub-sample period in the short run.

4. INVESTIGATIVE DESIGN AND OPTIMAL PORTFOLIO CONSTRUCTION METHODOLOGY

The daily stock price data is adjusted for stock splits and dividends for the sample periods. The daily data for portfolio optimization are collected for DIA and 30 Dow components for 46 days before September 30, 2022. This section provides an operational and workable framework for constructing optimal portfolios of components. The application incorporates the capital asset pricing model, ways to find the excess return to risk ratios and unsystematic risk measures. It finds specific weights for the optimal portfolio of components. It follows a sequence of steps to find the portfolio of components.

This study also examines the performance properties of DIA (SPDR et al.) as a proxy of the Dow Jones Industrial Average (DJIA) Index since the DIA as a market proxy is required in the optimization process. The technique used for finding the optimal portfolio was initially introduced by Elton, Gruber, and Padberg (1987) (EGP technique). The essential steps of the EGP technique are as follows. First, find the "excess return to beta ratios" for components and rank them from highest to lowest. This will rank the components in relative performance based on return per unit of systematic risk contained. Second, the nonmarket variance of each component is calculated by calculating the variance of the market proxy, or Dow Jones Industrial Average Index proxy, DIA (SPDR Dow Jones Industrial Average ETF). Then, it sets the cutoff ratio to include those components that qualify for the optimum mix. The optimum mix will consist of all components for which the individual component's "excess return to beta" ratio exceeds the cutoff rate. The model finds the individual component's C ratio by solving a mathematical objective function to maximize the tangency slope of excess return to the component's risk measure with the constraint that the sum of the proportions of individual components included in the mix equals one. The optimum cutoff ratio (C’) is determined by finding the last individual component's C ratio, which is less than its "excess return to beta" ratio in the list of descending order of the excess return to beta ratios. After finding the qualified components for the optimum mix using the cutoff ratio (C’), calculate the percentage weight of each component for the optimal portfolio. The percentage of a component (Xi) in the optimum portfolio is:

$$X_i = Z_i / \sum_{i=1}^{n} Z_i * 100 \qquad (1)$$

where:

$$Z_i = [ß_i/\sigma_{ei}^2] * [TI_i - C'] \qquad (2)$$

Where:

σ_{ei}^2 = nonmarket variance of a component.

TI_i = Treynor Index of component = $(R_i - R_f)/ ß_i$,

R_f = risk-free rate,

R_i = the rate of return of component,

$ß_i$ = the systematic risk of component,

C’ = the optimum cutoff ratio.

After finding two separate, i.e., trailing and forward-looking optimal portfolios constructed from the Dow stocks as of September 30, 2022, this paper examines the performance of the trailing optimal portfolio and the forward optimal portfolio during the sub-sample period of 46 days after the event date of September 30, 2022.

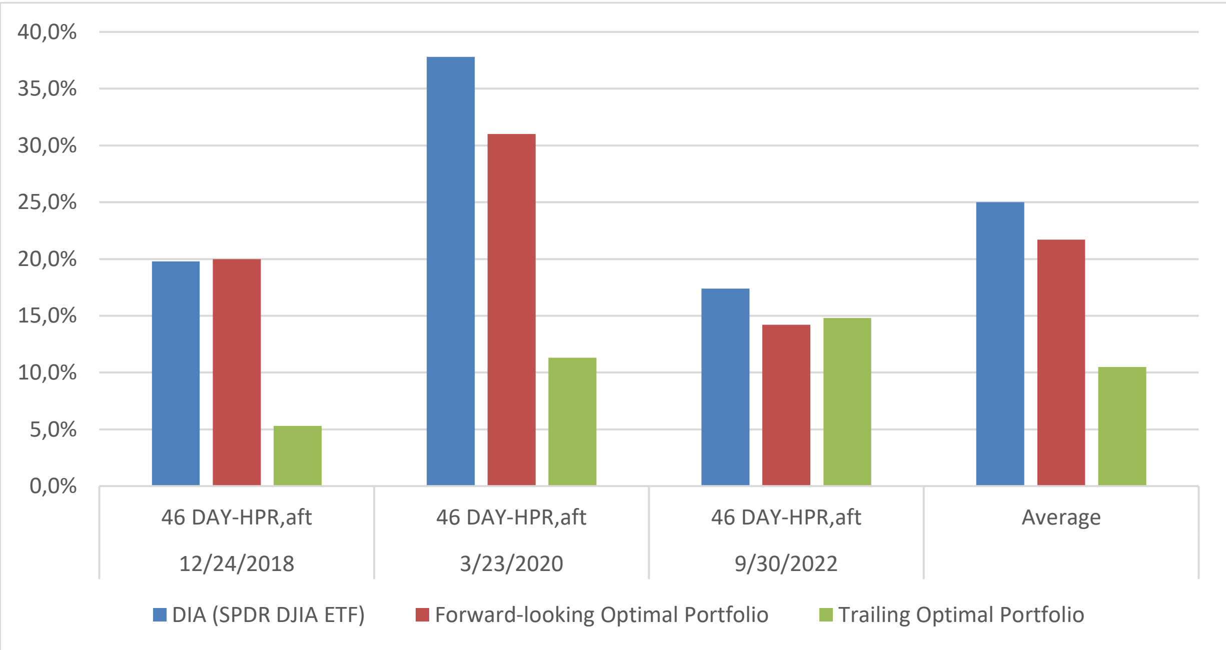
5. FINDINGS

Is the performance of the forward-looking optimal portfolios of stocks superior to that of the trailing optimal portfolios of DOW stocks? The answer is inconclusive if one considers the holding period return after the worst day of the 2022 case alone. As shown in Figures 1 & 2 and Tables 1 & 2, the HPR aft for the forward-looking EGP Optimal Portfolio (+14.2%) is slightly lower than the HPR,aft for the trailing EGP Optimal Portfolio (+14.8%). Interestingly, both HPR,afts are inferior to the HPR, aft of DIA (+17.4%). As shown in the last column of Table 2, the weighted-average performance rank of the Forward-looking portfolio was 21; the weighted-average performance rank of the Trailing portfolio was 20. Both are inferior to the rank of DIA (18). All portfolio components of the Trailing portfolio had lower group performance ranks in the second sub-sample period than in the first sub-sample period, i.e., 17 ranks lower. On the other hand, only two out of four components of the Forward portfolio have lower performance ranks in the second sub-sample period than in the first sub-sample period. The Forward portfolio had lower group performance ranks in the second sub-sample period than in the first, i.e., four ranks lower. The actual performance of the trailing optimal portfolio during the second half was +14.8%, which is inferior to the DIA’s performance of +17.4%. The trailing optimal portfolio was a group winner in the first half (the group rank, 3). However, the trailing optimal portfolio was a group loser in the second half (group rank, 20). Because the performance of the trailing EGP optimal portfolio is inferior to that of DIA, the practical usefulness of conventional backward-looking optimal portfolio construction has some limitations. Its hindsight is excellent, but its foresight is not great, at least in the short run. Nevertheless, the V-shaped recoveries of all three portfolios shown in Figure 2 are visibly dramatic.

There were two comparable findings, having examined the performance properties of trailing vs. forward-looking optimal portfolios using the same method. One examined the case related to March 23, 2020, when DJIA hit the lowest level in 2020. Another examined the case related to December 24, 2018, when DJIA hit the lowest level in 2018. Table 1 compares all three cases. Surprisingly, the performance of DIA turns out to be the best among the three compared. The average performance measures of all three cases are shown in the last column. DIA is the best performer (+25%), the forward-looking optimal portfolio is the second-best performer (+21.7%), and the trailing optimal portfolio is the worst (+10.5%). The finding of the comparatively superior performance of DIA is meaningful because it could mean a technical investment advantage, particularly after the worst day event.

Figure 3 and Table 3 show properties of the trailing optimal portfolio constructed as of September 30, 2022. It consists of WMT, JNJ, TRV, UNH, and MRK, with the top allocation being WMT (34.95% of the portfolio weight). As shown in Table 2, three out of five were loser stocks during the second half of the sample period. Figure 4 and Table 4 also show the forward-looking optimal portfolio constructed as of September 30, 2022. It consists of KO, MCD, VZ, and V, heavily favoring KO (55.4% of the portfolio weight). As shown in Table 2, the actual performance of the forward-looking optimal portfolio during the second half was +14.2%, which is inferior to the DIA's performance of +17.4%. The forward-looking optimal portfolio was a group loser in the first half (17) and a group loser in the second half (21). On the other hand, the trailing optimal portfolio was a decisive group winner in the first half (3) but a group loser in the second half (20). Therefore, the forward-looking optimal portfolio performed better than the trailing optimal portfolio in a relative sense if one considers the entire sample period.

Figure 1: Comparative Performance Properties of DIA, Forward-Looking and Trailing EGP Optimal Portfolios of DOW Stocks during 46 Days after Each of Three Event Days



Notes: 46 DAY-HPR, aft = Holding Period Return for 46 days after the lowest DJIA index level of the year.

Table 1: Comparative Performance Properties of DIA, Forward-Looking and Trailing EGP Optimal Portfolios of DOW Stocks during 46 Days after Each Of Three Event Days

Index/Portfolio	**12/24/2018**	**3/23/2020**	**9/30/2022**	
	46 DAY-HPR, aft	**46 DAY-HPR, aft**	**46 DAY-HPR, aft**	**Average**
DIA (SPDR DJIA ETF)	19.8%	37.8%	17.4%	25.0%
Forward-looking Optimal Portfolio	20.0%	31.0%	14.2%	21.7%
Trailing Optimal Portfolio	5.3%	11.3%	14.8%	10.5%

Notes: 46 DAY-HPR, aft = Holding Period Return for 46 days after the lowest DJIA index level of the year.

Figure 2: Comparative Performance Properties of DIA, Trailing, and Forward-Looking EGP Optimal Portfolios during 46 Days before and after September 30, 2022

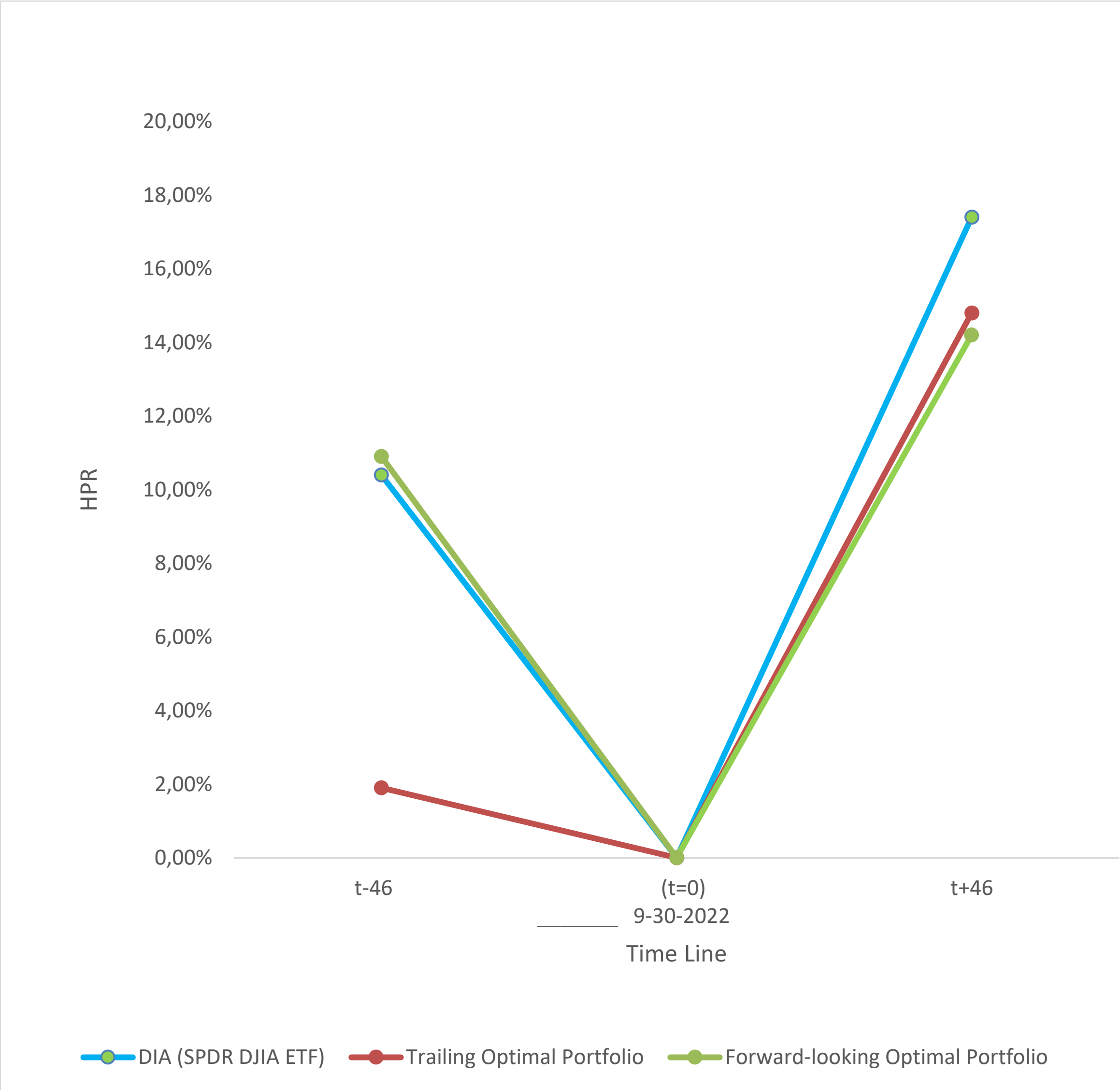


Table 2: Comparative Performance Properties of DIA, Trailing, and Forward-Looking EGP Optimal Portfolios during 46 Days before and after September 30, 2022

Index/Portfolio/Ticker	HPR,bef	HPR,aft	Rnk,bef	Rnk,aft
DIA (SPDR DJIA ETF)	-10.4%	17.4%	14	18
Trailing Optimal Portfolio Components & Weights:	-1.9%	14.8%	3	20
WMT (34.95%)	2.9%	15.6%	1	20
JNJ (28.07%)	-5.0%	8.5%	5	25
TRV (16.40%)	-3.1%	23.0%	3	11
UNH (11.66%)	-5.2%	7.1%	6	26
MRK (8.92%)	-4.8%	26.5%	4	8
Forward Optimal Port. Components & Weights:	-10.9%	14.2%	17	21
KO (55.40%)	-10.4%	14.0%	17	23
MCD (35.71%)	-10.4%	18.4%	15	15
VZ (8.76%)	-15.5%	-1.2%	25	29
V (.13%)	-15.4%	18.0%	24	16

Notes:
HPR = ((Ending Price – Beginning Price) + Dividend) / Beginning Price; however, in this study, the daily price data are already adjusted for dividends and stock splits, so the actual formula for HPR in this study is:
(Ending Adjusted Price – Beginning Adjusted Price) / Beginning Adjusted Price.
HPR,bef; Rnk,bef = Holding Period Return; Performance Rank for 46 days before SEPTEMBER 30, 2022, the benchmark day's lowest index level of the year.
HPR, aft; Rnk, aft = Holding Period Return; Performance Rank for 46 days after SEPTEMBER 30, 2022, the lowest index level 2022.
The performance measurements for DIA and optimal portfolios are rounded. Performance is based on closing prices adjusted for dividends and splits.

Figure 3: Properties of Trailing EGP Optimal Portfolio of DOW Stocks as of September 30, 2022

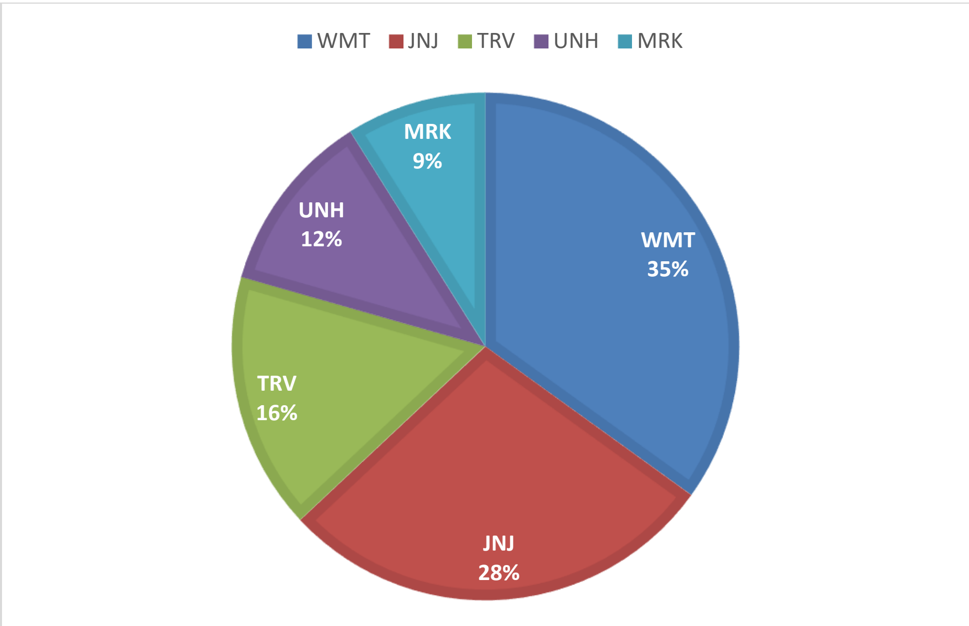


Table 3: Properties of Trailing EGP Optimal Portfolio of DOW Stocks as of September 30, 2022

Ticker	Wi
WMT	34.95%
JNJ	28.07%
TRV	16.40%
UNH	11.66%
MRK	8.92%

Notes: Expected Return Relative: .999641; Standard Deviation: .009436; Reward to Standard Deviation: -.038000; Correlation Coefficient: .50; Wi = Portfolio weight of component i.

Figure 4: Properties of Forward-Looking EGP Optimal Portfolio of DOW Stocks as of September 30, 2022

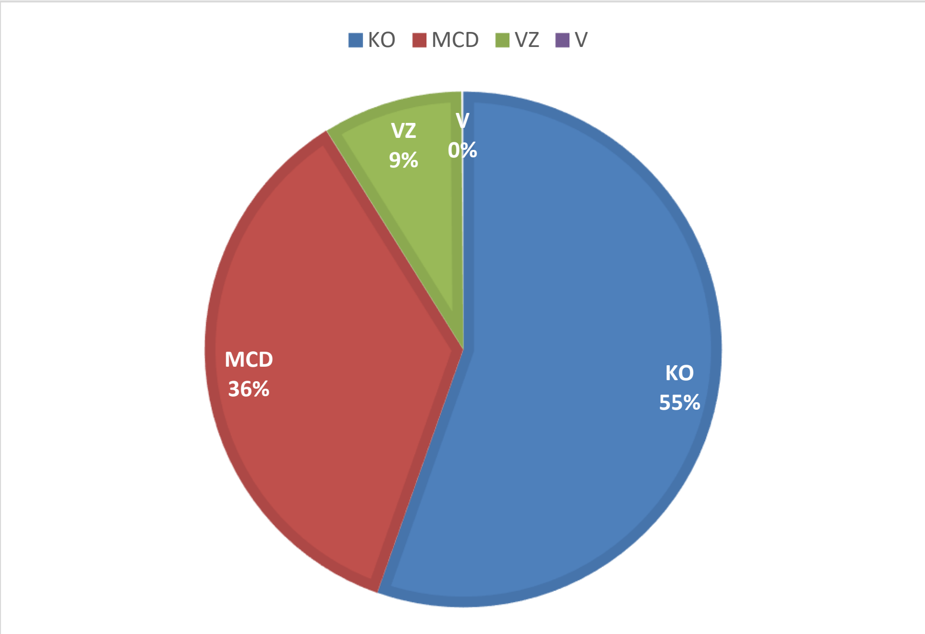


Table 4: Properties of Forward-Looking EGP Optimal Portfolio of DOW Stocks as of September 30, 2022

Ticker	Wi
KO	55.40%
MCD	35.71%
VZ	8.76%
V	.13%

Notes: Expected Return Relative: .997555; Standard Deviation: .009930; Reward to Standard Deviation: -.246216; Correlation Coefficient: .55; Wi = Portfolio weight of component i.

Figure 3 and Table 3 show the portfolio properties of the trailing EGP optimal portfolio, and Figure 4 and Table 4 show the portfolio properties of the forward-looking EGP optimal portfolio. Due to the heavy downturn of DJIA during the first half of the sample period before the worst-day event of 2022, the expected return relative was poorly low, less than 1 for both portfolios. The standard deviation of the trailing optimal portfolio (0.009436) was slightly lower than that of the forward-looking optimal portfolio (0.009930). The reward-to-standard deviation ratio for the trailing optimal portfolio was better than that of the forward-looking optimal portfolio. The correlation coefficient (0.50) for the trailing optimal portfolio was lower than the same property for the forward-looking optimal portfolio (0.55). So, all of the individual properties of the trailing optimal portfolio were better than the matching measures of the forward-looking optimal portfolio for the 2022 case.

6. CONCLUSION AND FURTHER STUDY

The positive reversal performance during the second half of the sample period after the September 30, 2022, event was apparent in all three: DIA, trailing optimal portfolio, and forward-looking optimal portfolio. The unexpected finding was the comparatively robust performance of DIA compared to the performance of two forms of optimal portfolios. It is fair to say that the worst-day events preserved the pricing efficiency of DOW stocks during the sample periods. That is, it is possible that the worst-day events did not disrupt the market efficiency for DOW stocks. This is because DIA, the market proxy of the DJIA index, performed the best, beating both forward-looking and trailing optimal portfolios in 2022 and, on average, of all three cases, as shown in Table 1. The only exception in Table 1 was that DIA performance in 2018 (+19.8%) was slightly lower than that of the forward-looking optimal portfolio in the same year (+20.0%). Therefore, DIA could give a winning opportunity to invest in DOW stocks after the worst day of the year event in the short run.

At the same time, forward-looking optimal portfolios for short-run investment in DOW stocks are a viable alternative to investing in the DIA, as evidenced by their performance superior to the performance of the trailing optimal portfolios on average. This study finds the usefulness of forward-looking portfolio optimization; however, it suggests a caveat of using trailing portfolio optimization for practical investment purposes. For further study, it would be worthwhile to consider a better fair value estimation in search of a better forward-looking portfolio optimization based on a more effective return-risk premise.

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FINANCIAL DISTRESS PREDICTION COMPETENCE OF THE ALTMAN Z SCORE AND ZMIJEWSKI MODEL: EVIDENCE FROM SELECTED ZIMBABWE STOCK EXCHANGE FIRMS

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ABSTRACT

Purpose- The study aimed to assess the predictive competence of Zmijewski X score and Altman Z score in detecting financial distress in two manufacturing companies that are listed on the Zimbabwe Stock Exchange. The purpose of the study was to ascertain which of the two models is better at foretelling financial distress. The study's conclusions may aid in improving practitioners' and academics' comprehension of the relative benefits of each model and their ability to forecast financial trouble and bankruptcy.

Methodology- The Altman Z score model was employed in the study as a yardstick measure to differentiate between the safe (Z >2.99), grey (1.81<Z<2.99), and distress (Z<1.81) zones for manufacturing organisations. An entity would be classified as bankrupt (X>0) or non-bankrupt (X<0) based on the Zmijewski X score, which was also employed in the research. Two manufacturing businesses registered on the Zimbabwe Stock Exchange made up the sample size for this study, which was carried out between 2010 and 2017. The research was dependent on secondary data gleaned from the two companies' financial statements.

Findings- Manufacturing firm 1's Z-score placed the firm in the distress zone in 2010 and the grey zone in the years 2011 to 2012. From 2010 until 2017, Manufacturing Company 2 experienced financial difficulties. The two manufacturing enterprises under investigation did not exhibit bankruptcy, according to the X-score statistics. According to the study's findings, the Z-score is a better indicator of financial difficulty in emerging nations than the X-score. The Altman Z score and Zmijewski X score models are both useful in predicting financial distress in firms. However, a limitation of these models is that they constitute different financial ratios (Z-score with 5 ratios and X-score 3 ratios) and interpretation. Despite this limitation, these models are still key in unearthing financial distress in firms.

Conclusion- The study concludes that the Altman Z score is superior to the Zmijewski X score in predicting financial distress in developing countries. The Altman Z score model uses 5 financial ratios to predict whether a company has a high probability of becoming insolvent. The Zmijewski X score model uses 3 financial ratios to predict bankruptcy. The study's findings are important for investors in protecting their investments as the model can help with informed decision making in terms of future prospects of the firm in terms of bankruptcy. There have been cases where an auditor provides an unqualified opinion of the financial statements of an entity only for the entity to be declared bankrupt after the release of the financial statements. Therefore, models such as the Altman Z score can aid in protecting investor loss as the tool can be used to determine bankruptcy, a key signal to divest from the company.

Keywords: Bankruptcy, signalling theory, Altman Z Score, Zmijewski X Score, manufacturing companies.
JEL Codes: M40, M41

1. INTRODUCTION

The Zimbabwe economic environment hasn't been favourable for firms. The local currency has lost considerable value with citizens preferring to hedge against inflation by storing value by acquiring United States of America dollars and investment in real estate. Hyperinflation has hampered borrowing as the Reserve Bank of Zimbabwe increased interest rates to 200% hence challenging to meet working capital needs. According to CZI (2011:8), Low output demand, equipment failure, inadequate operating capital, plus a shortage of primary commodities were the manufacturing industries' top capacity bottlenecks. major capacity constraints faced by the manufacturing sectors were low production demand, machine breakdown, lack of working capital and lack of primary commodities. CZI (2012:3) posits availability and cost of funding, power shortages, economic instability and high costs of labour and rigid labour laws as factors that negatively impacted capacity utilization. According to CZI (2014):15, the PMI is 43.5%, which indicates that the economy is weakening. Inconsistency in legislation, a decline in domestic product demand, competition from exports, easy access to capital, and corruption are the main factors influencing business in 2016. The shortage of foreign currency in 2019 as a result of the inadequate auction rate had a detrimental impact on the industrial sector. Because of the price indexing in USD, manufacturers therefore faced high raw material costs. Employees that participated in load shedding worked one shift. Low de The frequent power outages and lack of foreign cash for purchasing replacement components made the situation with outdated equipment and frequent equipment breakdowns worse. The lack of access to foreign cash by Local Authorities to buy water treatment chemicals caused the water shortages to worsen and reduced demand for goods as a result of declining disposable incomes brought on by rising inflation rates.

According to Confederation of Zimbabwe Industries (CZI, 2021), policy inconsistencies affect prediction of the operating environment. Zimstats (2022) postulates Purchasing Managers Index (PMI) stood at 30.3 points down from 35 points thus signalling manufacturing sector contraction. Therefore, capacity utilisation from 2009 to 2021 is as per table 1 below:

Table 1: Weighted Capacity Utilisation

Year	Weighted Capacity Utilisation %
2009	32.3
2010	43.7
2011	52.7
2012	44.9
2013	36.1
2014	36.5
2015	34.3
2016	47.4
2017	45.1
2018	48.2
2019	36.4
2020	47.0
2021	56.3

Ndlovu (2019) states 96 companies closed due to the harsh economic environment. Massive power outages, punitive interest rates for short term loans were some of the factors attributed for company failure as they impacted on manufacturing activities. Zimstats (2022) articulates raw material shortages, and cash flow challenges as some of the major constraining factors to production. The study pursued bankruptcy prediction comparative competence of Altman Z Score and Zmijewski model to identify the key financial distress model that can users of financial statements can adopt to analyse a firms's financial complication in terms of financial astuteness. In comparing the two models, the study answers the following research questions:

i. What is the level of financial distress of the selected manufacturing firms?

ii. Which model is the most accurate in determining financial distress of firms between the Altman Z Score and Zmijewski models?

iii. Which ratio within the Altman Z Score and Zmijewski models impact financial distress of the selected manufacturing firms?

2. LITERATURE REVIEW

2.1. Signalling Theory

According to Watts (2003), the theory underscores the significance of financial information furnished to users of financial statements concerning current and future prospects of the company in order for investors to inform on the financial information released in relation to the company. Therefore, in the context of bankruptcy, the theory advances companies will send signals, portraying bankruptcy or likelihood of bankruptcy. Togno (2010) studied the effect of financial distress signals in relation to bankruptcy prediction models and concluded that profitability, leverage and liquidity are crucial financial distress signals as the various users of financial statements are able to determine a company's financial vigour. Hutton and Marcus (2015) suggest activities like the issuance of equity, can signal company's financial distress thus leading to bankruptcy. Greco and Manca (2019) articulate the combination of financial ratio and signalling theory significantly impact accuracy of bankruptcy prediction models. The signals (good or bad) are important to users of financial statements in order to mitigate risk that is linked with bankruptcy.

2.2. ALTMAN Z SCORE

The Z score bankruptcy model was developed by Edward I Altman in 1968. Based on five financial parameters, the Altman Z-score is a formula that assesses a company's risk of insolvency. Leverage, liquidity, solvency, profitability, and activity ratios are all taken into consideration by the algorithm. A linear combination of four business ratios for private sector companies or five business ratios for manufacturing enterprises, weighted by coefficients, creates the Z-score. The model was stated as follows for manufacturing firms:

$$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 0.999X5$$

Where:
X1: Working Capital / Total Assets
X2: Retained Earnings / Total Assets
X3: Earnings Before Interest and Taxes / Total Assets
X4: Market Value of Equity / Book Value of Total Liabilities X5: Sales / Total Assets.
Z: Overall index

Firms that operate in the private sector utilize the following Z score model:

$$\text{Z-Score} = 6.56\ X1 + 3.26\ X2 + 6.72\ X3 + 1.05\ X4$$

Where:
X1: Working Capital / Total Asset
X2: Retained Earnings / Total Assets
X3: Earnings Before Interest & Taxes / Total Assets
X4: Market Value of Equity / Book Value of Total Liabilities

The variables of the model as explained below.

X1: Working Capital / Total Asset. Firms that regularly experience operating losses are likely to have dwindling current assets in comparison to total assets (Altman, 1968). To this effect, the ratio is a stringent measure of liquidity when compared to the current ratio or acid test/quick ratio.

X2: Retained Earnings/ Total Assets. Businesses that have more retained earnings relative to their overall assets often funded their assets through profit accumulation. (Altman, 1968). **X3: Earnings Before Interest and Taxes / Total Assets.** The ratio gauges' efficiency of an entity's assets, hence crucial in corporate failure research (Altman, 1968).

X4: Market Value of Equity / Book Value of Total Liabilities. The ratio signifies the extent to which the firm's property can fall in value before liabilities surpass assets leading to firm bankruptcy (Altman, 1968).

X5: Sales / Total Assets. The ratio measures the ability of the firm's assets to generate revenue (Altman, 1968).

2.3. Zmijewski

The Zmijewski X model was published in 1984 and utilises ratios to analyze financial performance, leverage and liquidity of entities. One indicator of a company's risk of insolvency is the Zmijewski score. Zmijewski created it and used it on 800 steady businesses and 40 failed enterprises. Metrics including financial liquidity, leverage, and performance are used to compute the score. The chance of the corporation filing for bankruptcy increases with the score. The model is as stated below.

$$\text{X Score} = -4{,}3 - 4{,}5X1 + 5{,}7X2 - 0{,}004X3$$

Where:
X1: Net Income / Total Assets
X2: Total liabilities /Total Assets
X3: Current Assets / Current Liabilities

The variables of the model are as explained below:

X1: Net Income/ Total Assets. A superior ratio indicates a better financial state for the organisation.

X2: Total liabilities / Total Assets. The ratio's magnitude indicates how financially healthy the firm is as it reveals an entity's aptitude in settling its debts with assets held.

X3: Current Assets /Current liabilities. A higher ratio indicates that the firm can pay its current commitments revealing superior company financial health.

2.4. EMPIRICAL LITERATURE REVIEW

Huyghebaert and Van de Gucht (2007) posit the Z-score outperformed the X-score in financial distress prediction of Belgian firms. Fatmawati (2012) suggests Zmijewski model (X-score) as unearthing greater precision than Altman model (Z-score) and Springate models. Avenhuis (2013) proposes X-score model as having greater precision than Z-score, and Ohlson O score based on 14 bankrupt and 326 non bankrupt companies from 2011 to 2012. In their comparative analysis of the Altman, Grover, Springate, and Zmijewski models, Fauzi, Sudjono, and Saluy (2021) find that the Altman Z Score is the most effective in forecasting financial difficulty. The Grover and Zmijewski model had erratic results. According to Supitriyani, Astuti, and Azwar (2022), when equated to the Springate, Grover, and Zmijewski model, the Altman Z score is the most precise. According to Viciwati (2020), the Zmijewski X Score model has a 90% accuracy rate for predicting insolvency. The Zmijewski model, according to Lutfiyyah and Bhilawa (2021), is 72% accurate in predicting financial problems in English league football clubs. When the Altman Z score, Zmijewski, and Springate models were examined by Yendrawati and Adiwafi

(2021) in the real estate industry, the Altman Z score's accuracy was greater than that of the Zmijewski and Springate models'. Different bankruptcy prediction models are investigated by Noor Salim and Ismudjoko in 2021. According to their investigation, the Altman Z Score and Ohlson models are more accurate at predicting financial hardship, with an accuracy rate of 90%. The precision level of the Zmijewski model was 86.36%, whereas that of the Grover model was 81.82%. The Springate model's prediction rate is the lowest, with 63.64%. According to Melina and Kalinggo (2023), the Altman Z score, Grover, and Zmijewski models did not significantly affect the ability to predict financial hardship for listed coal businesses listed on the Indonesian stock exchange between 2017 and 2021.In the automobile industry, Winarso and Edison (2020) examined bankruptcy prediction models based on the Altman Z score, the X-Score Zmijewski, the G-Score Grover, and the S-Score Springate. According to their research, the Springate S score outperformed the Altman Z score and Grover and Zmijewski models in terms of accuracy in predicting bankruptcy.

Sinarti and Sembiring (2015) suggest there exists significant differences between the Z-score and X-score in their study of 11 manufacturing firms. Chadha (2016) advances the Z-score unearthed 25.94% of 196 Kuwait Stock Exchange firms as being in financial distress from 2009 to 2014 with the X-score results being inconclusive. In Spain, the Z-score outperformed the X-score in financial distress prediction (Rovira and Blasco,2016). Fauzan (2017) postulates the Z-score accuracy as 46.67% and X-score error level of 100%. Edi and May (2018) unearths Z-score as superior to the X-score based on their research in Indonesia. According to Heusein and Pambekti (2014), the X-score is unsurpassed compared to the Z-score and Grover models. Salim and Sudiono (2017) postulate the X model as dependable than the Z score and Springate S score models in their study of 19 coal mines in Indonesia. Wang and Huang (2017) advance X-score and more effective in determining financial distress in the short term with Z-score in the long term. According to Huda, Paramita, and Amboningtyas (2018), the X-score has the greater precision with the least error rate when compared with Z score and Springate models in the retail sector on IDX 2013-2017. Anggraeni (2008) and Abadi (2017) reveal the Zmijewski model as incapable of detecting bankruptcy. Wanaya, Muliartha, Budiasih and Waratmaja (2020) posit the X-score as revealing greater accuracy with 80% when compared with the Z-score. The accuracy of the Z-Score, Springate, and Zmijewski models in forecasting financial distress circumstances of businesses in the real estate, property, and building construction sectors was compared by Yendrawati and Adiwafi (2020). All real estate firms that were registered with the Indonesian Stock Exchange between 2014 and 2018 were included in the study sample. The Altman Z-Score model, followed by the Zmijewski and Springate models, was shown to have the highest accuracy in predicting financial trouble in the property, real estate, and building construction sectors.

3.. METHODOLOGY

The study is descriptive in nature, estimating the degree of distress of the chosen enterprises across the study period using financial indicators and ratios. The analysis of the report focuses on two manufacturing companies that are listed on the Zimbabwe Stock Exchange. To investigate the financial distress of the involved enterprises, the Zmijewiski X score and Altman score are computed to identify any early warning indicators of financial distress that may be remedied over time. This study makes use of secondary data that was retrieved from the websites of the two manufacturing businesses that were chosen, as well as financial statement data for the years 2010 through 2017.

3.1. Models for Analysis

The study compares two corporate failure models and adopts the following models for financial distress analysis.

3.1.1. Altman Z Score

$$Z = 1.2_{X1} + 1.4_{X2} + 3.3_{X3} + 0.6_{X4} + 0.999_{X5} \quad (1)$$

X1: Working Capital / Total Assets
X2: Retained Earnings / Total Assets
X3: Earnings Before Interest and Taxes / Total Assets
X4: Market Value of Equity / Book Value of Total Liabilities X5: Sales / Total ssets.
Z: Overall index

Model interpretation; Z < 1.81 Distress zone, 1.81< Z < 2.99 Grey zone, Z > 2.99 Safe zone

3.1.2. Zmijewski Model

$$\text{X-Score} = -4{,}3 - 4{,}5\ _{X1} + 5{,}7\ _{X2} - 0{,}004\ _{X3} \quad (2)$$

X1 = Net income / Total Assets
X2 = Total Debt / Total Assets
X3 = Current Assets / Current Liabilities

Model interpretation; X > 0 Bankrupt, X < 0, Not Bankrupt

3.2. Accuracy of the Model

In order to determine the accuracy of the models, the following was utilised.

Accuracy of the model = (Total number of correct predictions / total sample) (100) (3)

4. RESULTS AND DISCUSSION

The ability to forecast a company's risk of financial hardship or bankruptcy makes bankruptcy models valuable. These models can provide information about a company's financial health and spot possible warning indicators of financial problems by examining a variety of financial ratios and other pertinent data. Decisions regarding the company's future can be made using this information by legislators, investors, and other stakeholders. To hedge against possible losses, investors may decide to sell their firm shares if a bankruptcy model indicates that the business is very vulnerable to financial trouble. In a similar vein, authorities may employ bankruptcy models to pinpoint businesses that face insolvency and implement measures to stop or lessen the effects of such occurrences on the whole economy. In general, bankruptcy models can lessen the likelihood of financial crises and serve to foster financial stability.

The study compared Altman Z Score and Zmijewski models in seeking to determine financial incapacitation of companies in a developing country. The results of the comparative analysis are as per table 2 and 3 below. are as tabulated below.

Table 2: Manufacturing 1 Altman Z Score

MNF 1	2010	2011	2012	2013	2014	2015	2016	2017
1.2X1	0.06	(0.024)	0.119	0.148	0.469	0.216	0.346	0.455
1.4X2	(0.186)	(0.290)	(0.160)	(0.052)	0.112	0.265	0.307	0.370
3.3X3	(0.690)	0.0630	0.330	0.393	0.508	0.571	0.399	0.505
0.6X4	1.175	0.920	0.952	2.363	3.113	4.747	5.146	5.168
0.999X5	1.041	1.259	1.676	1.439	1.227	1.126	1.012	0.938
Z SCORE	**1.400**	**1.928**	**2.917**	**4.291**	**5.429**	**6.925**	**7.210**	**7.436**

Table 3: Manufacturing 2 Altman Z Score

MNF 2	2010	2011	2012	2013	2014	2015	2016	2017
1.2$_{X1}$	(0.005)	(0.005)	(0.053)	(0.025)	(0.054)	(0.076)	(0.329)	(0.319)
1.4$_{X2}$	0.069	0.112	0.123	0.126	0.050	0.014	(0.260)	(0.298)
3.3$_{X3}$	0.050	0.175	0.099	0.109	(0.185)	(0.070)	(0.828)	(0.129)
0.6$_{X4}$	0.269	0.220	0.059	0.092	0.09	0.09	0.098	0.103
0.999$_{X5}$	0.102	0.150	0.180	0.147	0.116	0.118	0.167	0.128
Z SCORE	**0.485**	**0.652**	**0.408**	**0.449**	**0.017**	**0.076**	**(1.152)**	**(0.515)**

The Altman Z Score results for manufacturing company 1 (table 2) uncovers distress in 2010. In the years 2011 to 2012, grey zone and safe zone from 2013 to 2017. The Altman Z Score for manufacturing company 2 (table 3) reveals distress from 2010 to 2017. The distress zone is when Z < 1.81, 1.81< Z < 2.99 grey zone and Z > 2.99 Safe zone. A low Altman Z score indicates that a company may be more vulnerable to financial distress or bankruptcy, which could result in massive losses for its shareholders. Based on this, the results show that manufacturing company 1 is more liquid than manufacturing company 2. Manufacturing company 2 investors holding onto its shares could experience losses on their investment as a result of the liquidity challenges the firm has been facing. Investing in an illiquid company carries some risk because it may be difficult to sell your shares if you need to liquidate your investment quickly, but it can also present opportunities for higher returns if the company performs well over the long run. Prior to making an investment in an illiquid company, it's critical to assess the firm's development potential, management group, and financial standing.

Table 4: Manufacturing 1 Zmijewski Model

MNF 1	2010	2011	2012	2013	2014	2015	2016	2017
Constant	(4.3)	(4.3)	(4.3)	(4.3)	(4.3)	(4.3)	(4.3)	(4.3)
4.5X1	(0.599)	(0.351)	0.441	0.261	0.482	0.630	0.230	0.468
5.7X2	0.371	0.433	0.701	1.180	0	0.479	0	0
0.004X3	0.004	0.004	0.005	0.004	0.008	0.007	0.009	0.010
X SCORE	**(3.326)**	**(3.512)**	**(4.035)**	**(3.377)**	**(4.774)**	**(4.444)**	**(4.521)**	**(4.758)**

Table 5: Manufacturing 2 Zimjewski Model

MNF 2	2010	2011	2012	2013	2014	2015	2016	2017
Constant	(4.3)	(4.3)	(4.3)	(4.3)	(4.3)	(4.3)	(4.3)	(4.3)
4,5 $_{x1}$	0.0686	0.153	0.054	0.032	(0.464)	(0.126)	(0.894)	(0.145)

5,7 x_2	0.1995	0.285	0.023	0.593	0.730	0.713	1.000	1.081
0,004 x_3	0.004	0.004	0.002	0.003	0.002	0.002	0.007	0.006
X SCORE	**(4.165)**	**(4.164)**	**(4.329)**	**(3.736)**	**(3.104)**	**(3.459)**	**(2.399)**	**(3.068)**

The Zmijewski X Score for manufacturing company 1 and 2 (table 4 and 5) does not expose bankruptcy for the years 2010 to 2017 as the outcome is less than zero. According to X score, X < 0, the 2 manufacturing firms are not in financial distress or near bankruptcy.

4.1. Accuracy of the Model

According to table 6 and 7 below, the Z-score is a superior financial distress model as X-score failed to detect bankruptcy from 2010 to 2017 compared to the Z-score that detected financial distress in manufacturing company 2 from 2010 to 2017 and manufacturing company 1 in 2010 with 2011 to 2012 in the grey zone and 2013 to 2017 in the safe zone. Manufacturing company 2 was placed under judicial management in 2015 with final judicial management in 2016 in accordance with notices to shareholder obtained from the company's website. This further validates the accuracy of the Altman Z Score based on research findings and model accuracy statistics below in table 6. The findings are in agreement with Huyghebaert and Van de Gucht (2007), Fauzi, Sudjono, and Saluy (2021), Supitriyani, Astuti, and Azwar (2022), Yendrawati and Adiwafi (2021), and Noor Salim and Ismudjoko (2021) who advance the Z-score as a superior financial distress predictor than the X score.

Table 6: Altman Z Score

Years	Number of Correct predictions (Distress Zone)	Grey Zone	Safe zone	Sample	Level of accuracy
2010	2			2	100%
2011	1	1		2	50%
2012	1	1		2	50%
2013	1		1	2	50%
2014	1		1	2	50%
2015	1		1	2	50%
2016	1		1	2	50%
2017	1		1	2	50%

Table 7: Zmijewski X Score

Years	Number of Correct predictions (Bankrupt)	Not Bankrupt	Sample	Level of accuracy
2010		2	2	0%
2011		2	2	0%
2012		2	2	0%
2013		2	2	0%
2014		2	2	0%
2015		2	2	0%
2016		2	2	0%
2017		2	2	0%

4.2. Theory Implications

The study confirms the signalling theory through signals (good or bad) contained the published financial statements. These signals assist users of financial statements in risk management to protect their current and future investments as the signals can be that the company is bankrupt or is not bankrupt. The Z-score for manufacturing company 1 exposes entity as in the distress zone in 2010 and grey zone in 2011 to 2012. Manufacturing company 2 was in financial distress from 2010 to 2017. The signals would ideally protect the investments of stakeholders in terms of further investment, withdrawing further funding to the company, and attracting new capital.

5. CONCLUSION

The study used two manufacturing companies registered on the Zimbabwe Stock Exchange between 2010 and 2017 to evaluate the Z-score and X-score models for identifying insolvency. Z-score results for manufacturing company one uncovers distress in 2010. In the years 2011 to 2012, grey zone and safe zone from 2013 to 2017. The Z-score for manufacturing company 2 revealed distress from 2010 to 2017. The X-score results did not unearth bankruptcy in the two manufacturing companies. The study advances the Z-score as superior to the X-score as predictors of financial distress in developing countries. The two models can be significant to users of financial statements in order to limit bankruptcy risk to a minimum in terms of their possible investments. A limitation that is inherent in the models is that they constitute different financial ratios (Z-score with 5 ratios and X-score 3 ratios) and interpretation though they are key in unearthing financial distress in firms.

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INTRODUCTION TO THE POVERTY REDUCTION STRATEGY PLANS (PRSP): PROCESS AND EFFECTIVENESS REVIEW

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ABSTRACT
Purpose- This study tries to describe a comprehensive overview of the Poverty Reduction Strategy Plan papers. This is a crucial document that any current economist should understand. Currently, the globe is implementing seventeen development goals listed on the Sustainable Development Goals Agenda.
Methodology- The empirical review through several reports and works that addresses several themes that are pertinent to the Poverty Reduction Strategy Plans document, including the Interim Poverty Reduction Strategy Plan (IPRSP) and the Complete Poverty Reduction Strategy Plans (PRSP) was done. The work also describes how historically the concept of poverty reduction strategy plans (PRSP) came to exist. It covers the time from when the PRSP method was presented in 1999 up to date. Also, the work explains the main principles that must be included in preparing the Poverty Reduction Strategy Plans (PRSP) documents and challenges that face poor countries in the implementation of their corresponding poverty reduction strategy plans (PRSP) is discussed.
Findings- The paper finalize by looking at different discussions and views on whether these plans really help the poor countries, or they are just another mode of empowering the poor countries and international finance institutions will be given. By the end of this review a reader should be able to grasp and overview of overall concept of the poverty reduction strategy plans.
Conclusion- The study concluded that the plans help developing countries due to noticeable development progress in developing countries.

Keywords: Poverty, development, aids, economic development, Africa.
JEL Codes: I30, F63, F33, N47

1. INTRODUCTION

Poverty is a multifaceted challenge that has existed for more than two decades. The concept of the (PRSP) has been used to solve the poverty problem and consequently has become very common (Noël, 2006). These strategy plan (PRSP) was primarily developed by the International Monetary Fund (IMF) and the World Bank (WB) for developing or poor countries (Jim, 2002). Although developed countries, such as the United Kingdom (UK), began to implement these strategies before the 1990s (Chantal, 2007). In developed countries, these strategic plans are called National Action Plans on Social Inclusion. The main goal of these strategies is to provide a road map for poor countries to eradicate poverty with the help of development partners (Marlier et al., 2005).

In general, poverty reduction strategy plans (PRSP) handle poverty via three primary techniques: fostering access to opportunity, facilitating empowerment via good governance, and enhancing security through investments in human capital such as the health and education sectors (Craig & Porter, 2003). They essentially outline what a nation's structural, social initiatives and policies aimed at promoting economic growth and reducing poverty over a three-year period using key foreign funding sources (World Bank, 2001).

The International Monetary Fund (IMF) and the World Bank (WB) created loan-based poverty reduction policies that act as a base for development assistance to nations in need, providing cheap interest and debt relief. Countries get these loans on the condition that they fall into the category of Highly Indebted Poor Country (HIPC) and file the Poverty Reduction Strategy Paper (PRSP). The Poverty Reduction Strategies Plans (PRSP) are supposed to be country-driven, locally owned, and developed through broad participatory processes involving local government and civil society communities to facilitate implementation and surveillance (Hunter et al., 2003).

1.1. The Definition, Concept and Objectives of the Poverty Reduction Strategy Plans (PRSP)

Simply defined, poverty reduction strategy plans are policy booklets issued by borrower nations (poor countries) that include economic, social, and structural measures aimed at reducing poverty over a three-year or longer period. These plans serve as the primary vehicle for implementing the World Bank's long-term new approach to financing practices, which focuses on poverty reduction and empowers borrower nations to own and manage their own development agenda (Stewart & Wang, 2003).

Plans for reducing poverty have been mandatory for recipients of debt relief programs since 1999. These programs include the Heavily Indebted Poor Countries (HIPCs), Concessional International Development Association (CIDA) lending, and the Poverty Reduction Growth Facility (PRGF) of the International Monetary Fund (IMF). All these official plans are funded by the International Monetary Fund and the World Bank. Throughout the implementation phase, nations that are included in the Heavily Indebted Poor nations initiative (HIPC) would either get full loan cancellation or some other kind of financial assistance (Stewart & Wang, 2003).

The Poverty Reduction Strategy Plans (PRSPs) materials are mostly national property. It stressed that Poverty Reduction Strategy Plans (PRSPs), which target poverty and growth, should be created by borrower nations and authorized by World Bank (WB). In order to achieve maximum impact on poverty levels, the Poverty Reduction Strategy Plans (PRSPs) should be a program based on need, regardless of resources available, while taking nations' resources into consideration (WHO, 2004)

1.2. The Objective of Poverty Reduction Strategies

The primary purpose of the (IMF) and the (WB)'s Poverty Reduction Strategies Plans is to assist impoverished nations in developing and implementing effective poverty-reduction strategies. This primary aim can be met by achieving other minor goals, such as improving the relationship between debt relief and poverty reduction, and, lastly, ensuring that development partners' aids are employed more efficiently (Bretton Woods Project, 2003). The Poverty Reduction Strategy Plans (PRSPs) attempts to employ debt relief funds for poverty reduction purposes through several programs (Bretton Woods Project, 2003)

1.3. The Background of the PRSP

1.3.1. The Poverty Eradication Efforts from 1960 to 1980

When most African nations acquired independence in the 1960s, they had great prospects for future prosperity and development. Governments, with the assistance of donors, concentrated on catching up with industrialized nations by prioritizing industrialization as the fundamental source of economic growth. To lessen the country's overwhelming reliance on imported commodities, the Import Substitution Industrialization (ISI) system was implemented. Agriculture is the most important sector in this system since it provides raw materials and generates cash to fund other economic sectors in countries (Acemoglu et al., 2001).

Countries also thought that government control of the private sector was necessary to enhance it. As a result, most nations took a socialist strategy to development, in which the government controlled all elements of the economy. As a result, governments made significant investments in government-owned companies, imposed price controls on goods, and limited free commerce, credit, and foreign Exchange (Francis, 2003)

The socialist political strategy brought about major improvements in skilled labor, infrastructure, health, and education. However, the economic growth of African nations began to fall in the 1970s, and eventually economies were not performing well in comparison to other parts of the world. As a consequence, there was poor social conditions, a rise in debt, and bad economic performance. In addition, it resulted in large budget deficits, a payment imbalance, and a notable rise in the national debt (Franz et al., 2004).

African leaders, with the assistance of foreign financial institutions, suggested many remedies to the issue in the late 1970s. The first proposed solutions were the projects known as the Lagos Plan of Action (LPA) and the Regional Food Plan for Africa (AFPLAN) which were developed in 1955 during the Bandung Conference. The goal of these programs was to create middle-income countries in the Third World capable of addressing underdevelopment issues. Most African nations' institutional deficiencies made implementation difficult. In addition to institutional flaws, the communist approach made it impossible for most nations to meet the Bank (WB) and the (IMF) standards (Heidhues & Obare, 2011).

These strategies failed, and a second option was proposed based on a neoliberal philosophy of economic development. The solution comes from the World Bank's Berg Report (1981), called Towards Rapid Growth in Sub-Saharan Africa. According to the report, African governments and enforced policies are to blame for the continent's failure to prosper economically. The study suggested that governments refrain from meddling in commerce and currency exchange. This approach was followed by the implementation of conditional structural adjustment loans and sectoral adjustment loans, sometimes known as the Structural Adjustment Programs (SAPs) (Heidhues & Obare, 2011).

1.3.2. The Structural Adjustment Programs (1980-1999)

Structural Adjustment Programs (SAPs) were established in the 1980s to enhance agricultural, food, and nutrition in low-income countries. These policies were the result of the World Bank's (WB) and International Monetary Fund's (IMF) efforts to solve Africa's economic crisis during the 1970s. They became in effect between 1980s and 1990s. The Structural Adjustment Programs (SAPs) were designed to solve Africa's economic development difficulties, such as poor public sector management, which led to poor choices regarding investments and infrastructure (Heidhues & Obare, 2011).

In general, Structural Adjustment Programs (SAPs) focused on trade liberalization to improve impoverished nations' balance of payments systems and reduce their foreign borrowing

(Franz et al., 2004). Despite receiving financial backing from the International Monetary Fund (IMF) and the World Bank (WB), the Structural Adjustment Programs (SAPs) did not have the intended economic impact on development and food security. This was owing to inadequate policy implementation in low-income communities, a lack of ownership, and political will to enact policies (Heidhues & Obare, 2011)

1.3.3. The Adoption of PRSP

The Poverty Reduction Strategies Framework was adopted following the collapse of what termed as the Enhanced Structural Adjustment Facility (ESAF), that was established by the Britton Wood Institutions to assist low-income nations. The (ESAF) required low-income countries to develop Policy Framework Papers (PFPs). The review of the (ESAF) failed and did not achieve its stated aims due to a lack of national ownership, inadequate analysis of policy contents, and insufficient attention to policy trade-offs, as with prior programs (Segura et al., 2004)

In 1995, James Wolfensohn, who was the president of the World Bank, proposed a new agenda that emphasized consultation with NGOs and development partners. As impoverished nations increased their demand for debt relief, the World Bank and IMF conducted the (HIPC) studies on how debt relief may be utilized to eliminate poverty. To solve this issue, the Poverty Reduction Strategies Plan (PRSP) appeared to be the appropriate approach. Several NGO initiatives, including Jubilee 2000 and The Strategic Partnership with Africa, contributed significantly to the formation and funding of the Highly Indebted Poor Countries Initiative (HIPC II). Finally, in September 1999, the (IMF) and the (WB) established the PRSP strategy (Driscoll & Christiansen, 2004).

The Poverty Reduction Strategies replaced the Policy Framework Papers (PFPs) to increase country ownership of development programs and foster closer coordination between the Britton Woods Institutions and development partners. Other objectives were to increase public responsibility and action. The new PRSP method focuses on building a country-owned process with wide involvement in order to create successful poverty-reduction measures (Segura et al., 2004).

Despite the fact that the structural adjustment programs and the PRSP have many similarities in the sense that they are all global efforts targeting developing countries to eradicate poverty and improve the economic situation, these two approaches differ in many ways. These differences among them can be observed in areas such as the specified target economies of the SAPs and PRSP and the primary goal toward the application of the approaches.

2. The Contrast of the Structural Adjustment Program and the PRSP

The World Bank's Poverty Reduction Strategies Plans (PRSP) are a new framework for providing economic help to marginalized nations. The Poverty Reduction Strategy regime launched in the 2000s and is regarded to be the predecessor regime of the old Structural Adjustment Program or Lending. These aids can be Poverty Reduction Strategy Credits (PRSC), project loans, grant aid, and, in some cases, technical aid such as the Structural Adjustment Programs (SAPs). The (SAPs) is an old aid program that started around 1980s and ended in the late 1990s. Despite likenesses between these two techniques or regimes, Ishikawa (2003) noted the following differences

To begin, the Structural Adjustment Programs was created to help all developing nations, regardless of economic level, but the Poverty Reduction Strategy Plans are primarily intended to aid low-income countries. Second, whereas the structural adjustment lending regime's primary purpose was to enhance economic development, and poverty eradication was viewed as a byproduct of growth, the Poverty Reduction Strategies' primary goal is poverty elimination, with growth viewed as only one of several end effects. Third, the conditions in the structural adjustment program or financing (SAP) are ex ante, whereas the conditions in the Poverty Reduction Strategies Approach (PRSP) are ex post (Ishikawa 2003).

2.1. Underpinning Principles of Poverty Reduction Strategy Plans (PRSP)

According to the World Bank's Comprehensive Development Framework (CDF), there are five major concepts to consider while developing Poverty Reduction Strategies (PRSP). Briefly, they are as follows:

Plans must be owned by a country: The phrase "owned by a country" does not mean that the responsible ministry must merely sign the paperwork. It essentially entails the cooperation of many ministries, parliamentary bodies, and local governments. It also advocates broad participation from civic society, women, ethnic minorities, research institutes, academic institutions, the commercial sector, and labor unions. Internal and external development partners (Levinsohn 2003). This concept states that Poverty Reduction Strategy Plans (PRSP) should be owned and controlled by the country's own government. This indicates that the Poverty Reduction Strategy Plans (PRSP) should be established with broad participation from civil society and the commercial sector at all stages. The Principle of Poverty Reduction Strategy Plans (PRSP) (Driscoll & Christiansen, 2004).

The Plans (PRSP) must be result-oriented: The Poverty Reduction Strategy Plans (PRSP) must prioritize and focus on outcomes that help those in need. To accomplish outcomes, the plans (PRSP) should be developed within a shared budgetary framework (Harrison et al., 2003). This concept tries to avoid the mistakes committed in the prior approach to lowering poverty rates before 1999. The accountable parties participating in the formulation of the (PRSP) must guarantee that the plans have an impact on individuals in need (Levinsohn 2003).

The plans (PRSPs) must be extensive and long-term in scope: Poverty Reduction Strategy Plans (PRSP) should include macroeconomic, structural, sectorial, and social components, as well as understand the multidimensional character of poverty throughout time. After 3-5 years, Poverty Reduction Strategy Plans (PRSP) should be reviewed and revised (Harrison et al., 2003).

The Plans (PRSP) must have priorities: To make Poverty Reduction Strategy Plans (PRSP) possible, prioritize execution in budgetary and institutional terms (Driscoll & Christiansen, 2004)

Poverty reduction strategy Plans (PRSPs) must be partnership-focused: To improve decision-making accountability, the (PRSP) should be developed in partnership with bilateral, multilateral, and non-governmental organizations. The goal of this method is to establish joint responsibility amongst development partners (Harrison et al., 2003).

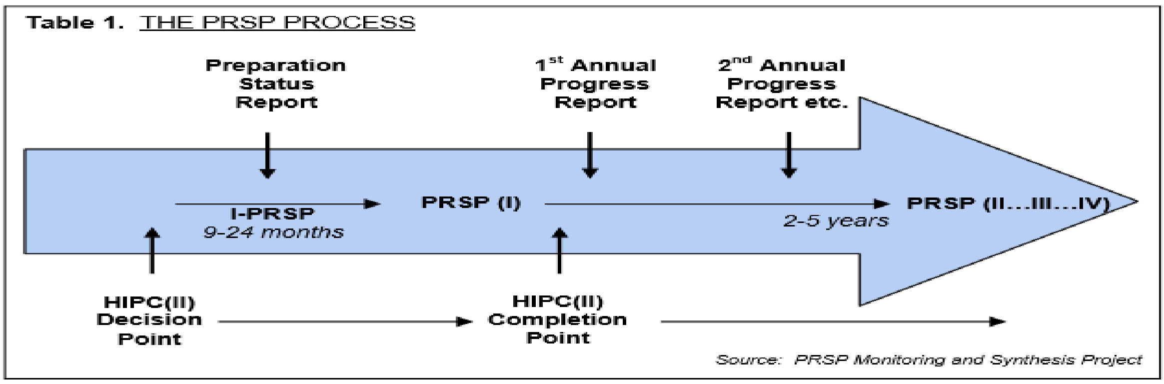
3. The Preparation of Poverty Reduction Strategy Plans (PRSP) Cycles and Structures

Countries take different approaches to establishing Interim Poverty Reduction Strategies Plans (IPRSPs), full Poverty Reduction Strategies Plans (PRSPs), and accompanying PRSP evaluations. However, the processes match in all nations. Because of the collaborative nature of the plans, the preparation process takes a long time to achieve the high quality that donors expect. The Poverty Reduction Strategies Plans (PRSP) preparations result in three official papers. These papers include interim Poverty Reduction Strategy Plans, a complete paper of poverty reduction plan, and an evaluation of the poverty reduction strategy (Hughes & Haworth, 2011).

The preparation procedures of the (PRSP) begins with an Interim Poverty Reduction Strategy Plan (IPRSP). This paper is created before Poverty Reduction Strategies Plans (PRSPs). Its goal is to establish and clarify a country's existing poverty-reduction programs, and blueprint or road map for the development of comprehensive Poverty Reduction Strategy Plans (PRSP). It is typically created by the Ministry of Finance under the direction of the main government, with input from other development partners. The time it takes to prepare the entire Poverty Reduction Strategy Plan (PRSP) after receiving the Interim Poverty Reduction Strategy Plans (IPRSP) ranges from 9 to 24 months (Driscoll & Christiansen, 2004).

The (IMF) and (WB) assess both papers (interim and comprehensive Poverty Reduction Strategies Plans (PRSP)) and submit evaluation reports to the Joint Staff Assessments. The assessments include comments and suggestions that explain if the country is entitled for a concessional loan or debt relief. A country's debt is first reduced after submitting Interim Poverty Reduction Strategy Plans (IPRSP), and then again after submitting the complete (PRSP). The (IMF) and (WB) demand countries to file Annual Implementation Reports (APRs) that detail the operation of the Poverty Reduction Strategy Plans (PRSPs). These strategies must be reviewed and assessed every two or five years in order to improve (Driscoll & Christiansen, 2004).

Figure 1: Poverty Reduction Strategy Plan

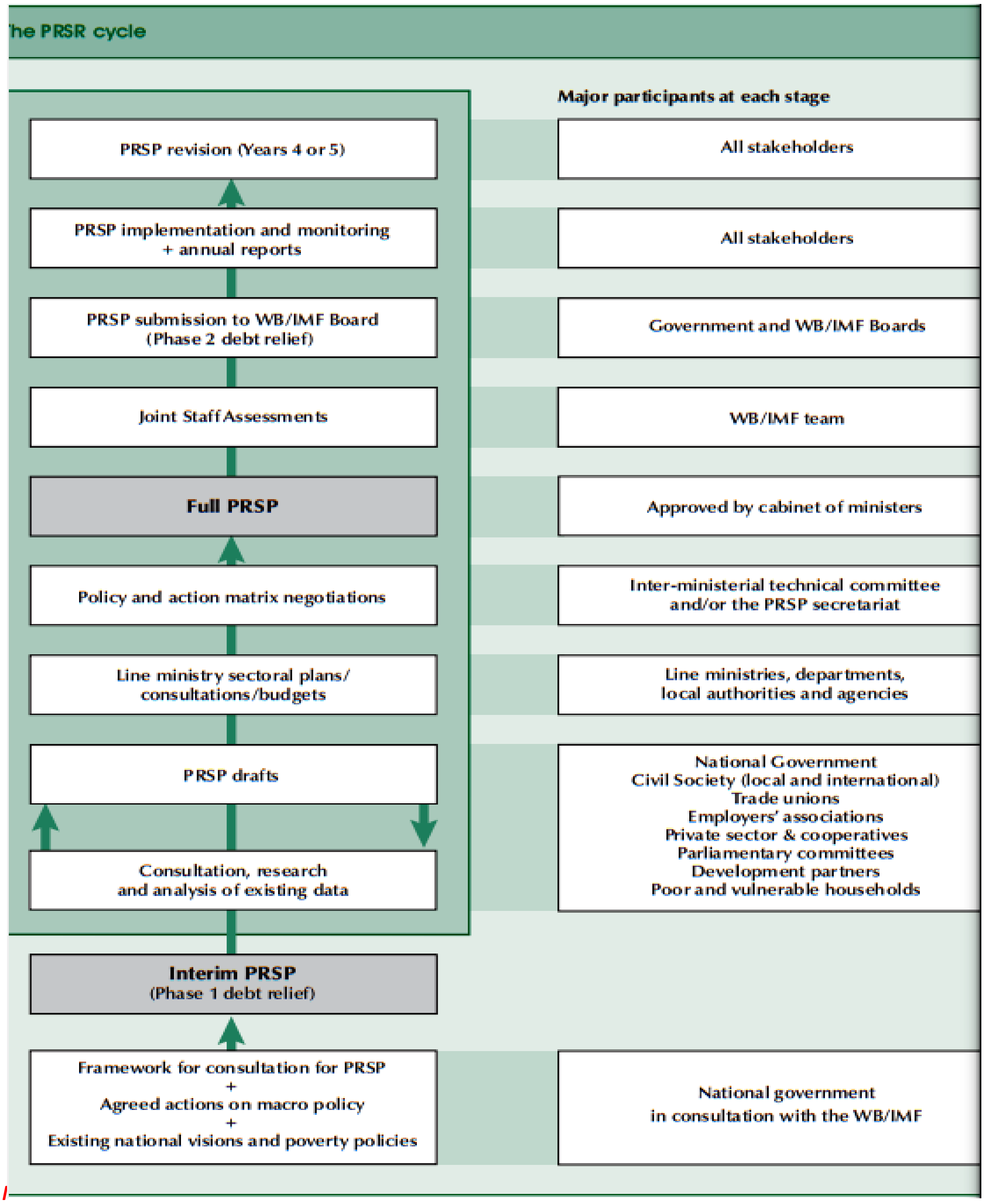


Source: (Driscoll & Christiansen, 2004).

3.1. The Main Actors (participants) of the (PRSP)

The government plays the key role in the process, which entails extensive institutional discussions. Following the consultation, the agreements achieved are formally documented by government officials who are specialists in the subject. The consultation phase often occurs in the writing the Interim Poverty Reduction Strategy Plan (IPRSP), the complete (PRSP), and the review of the (PRSP). Most governments have particular committees or agencies in charge of implementing and overseeing the Poverty Reduction Strategy Plan (PRSP) (Hughes & Haworth, 2011).

Figure 2: Players or actors involved at each step of the (PRSPs) development process



Sources: (Hughes & Haworth, 2011)

3.2. Assumptions of the Formations and Implementation of the Poverty Reduction Strategy Plan (PRSP)

Typically, the Poverty Reduction Strategy Plan (PRSP) is thought to be a technocratic document. This is because the primary actors in this method (the International Monetary Fund and the World Bank) required that the paper be non-political. The Poverty Reduction Strategy Plan (PRSP) is primarily driven by political procedures. Based on this fact, the following are the three fundamental assumptions that support its formulation and implementation (Craig & Porter, 2003).

Poverty alleviation is a political process: Any Poverty Reduction Plan must include powers, partnerships, access to state or national resources, and sectoral laws and regulations. All these elements are accessible or done under the influence of politics. To properly implement the Plan (PRSP), the stated variables must be changed and used in a way that allows impoverished people to establish long-term, good livelihoods.

The Plan (PRSP) seeks to influence local and domestic political processes: The success or failure of poverty reduction initiatives in poor nations is determined by the effectiveness of the state's political structure. Accountability, representativeness, adequate institutionalization, and responsiveness are all factors that influence the state's political efficacy. If the government is ineffective, the plan (PRSP) goals may not be met due to weak institutionalization, accountability, ineffectiveness, or representativeness.

The Plan (PRSP) proposes altering power dynamics between poor and affluent nations: Poverty reduction schemes, such as the SAPs, have historically failed as an outcome of the execution of conditional policies. As a result, there was no balance between wealthy and poor countries. The introduction of the Plan (PRSP) implies that development partners and donors should now focus on policy processes aimed at increasing the effectiveness of development aid and restoring power balances between rich and poor countries, rather than conditionality.

3.3. The Myths Surrounding the Plans (PRSP)

The Plans (PRSP) have advocates, but they also have detractors who do not trust in their foundation and ideas. Supporters of the Plan (PRSP) are accused of misrepresenting the reality, claiming that the PRSP is a miracle solution to the long-standing puzzle of poverty in underdeveloped nations. According to (Driscoll & Christiansen, 2004) there are three misconceptions that may be labeled as follows

The End of Conditionality: It should be noted that previous poverty-eradication initiatives, such as the Structural Adjusted Program, failed owing to the huge constraints tied to the enforced policies. As a result, the Poverty Reduction Strategies Plans (PRSP) that followed the failure of the SAPs are not a novel concept. It is the same concept that was developed using the lessons acquired from the previous unsuccessful Structural Adjusted Program (SAP). This indicates that the Poverty Reduction Strategies Plans (PRSP) did not remove the constraints associated with debt relief and concessional loans. It simply shifted the attention to the policy process rather than the status of specific policies.

Silver bullet technology. The term "silver bullet technology" refers to something that provides a miraculous and quick solution to issues, or long-time mystery such as poverty. The Poverty Reduction Strategies Plan (PRSP) is not a technological tool that can solve every problem perfectly. However, it is just a tool that focuses on changes affecting a large portion of civil society.

The overnight sensation. One of the important basics of the Poverty Reduction Strategies Plan (PRPS) is that it be long-term. The term "overnight sensation" refers to Poverty Reduction Strategies Plans' (PRPS) ability to achieve its intended aims immediately. In actuality, the Poverty Reduction Strategies Plan (PRSP) strategy does not offer a quick fix to a complicated problem that has remained unresolved for years.

4. ESSENTIAL COMPONENTS OF A POVERTY REDUCTION STRATEGY PAPER

According to the World Bank, (2000) the (PRSP) strategy aims to strengthen the fundamental concepts of country ownership, holistic development, and broad public engagement. Unfortunately, there is no blueprint. Countries differ in how they structure their poverty reduction strategies. Although these strategies must be comparable, The World Bank recommends the following basic aspects for every poverty reduction strategy plan:

Identifying the hurdles to poverty reduction and growth: Normally A poverty reduction strategy begins with a brief introduction and description of who the poor are, where they live, and which vulnerable areas should be improved. This is often accomplished by examining current macroeconomic, social, structural, and institutional evaluations to suggest strategies to accelerate growth and eliminate poverty.

Policies and objectives: Every Poverty Reduction Strategy Plan (PRSP) should have policies and matching targets. Through these policies, one may gain a better knowledge of poverty and its causes. In addition, Poverty Reduction Strategy Plans (PRSP) should specify the medium-term goals and long-term goals that must be realized through a country's Poverty Reduction Strategy Plans.

Monitoring: To ensure that Poverty Reduction policies, including short- and long-term objectives, are smoothed and implemented, a Poverty Reduction Strategy should include a framework that outlines how monitoring progress will be made. It should also explain how implementation progress will be communicated to development partners.

External aid: To increase donor compliance, countries must align their policies and long- and short-term goals with the total government budget. As a result, the Poverty Reduction Strategies Plan (PRSP) should specify the amount of external financing and technical assistance required from development partners to carry out the plan.

Participatory process*:* A plan (PRSP) must also include information on the structure, intensity, and location of the consultation process used to prepare the strategy's materials. In this section, the major topics and concerns mentioned by participants will be summarized.

4.1. Challenges that Face the Plans (PRSPS)

The IMF and the WB presented the idea for Plans (PRSP) to impoverished nations as a requirement for receiving debt reduction and economic assistance over two decades ago. The Plans (PRSPs) is largely sponsored by the United Nations (UN), international organizations, financial contributors, and civil society groups worldwide. By 2010, over 140 nations were already constructing their Poverty Reduction Strategies (PRSP), beginning with the Interim Poverty Reduction Strategy Plan (IPRSP), while other nations were well into the third cycle of their PRSP (Khan, 2010).

The primary purpose of the Plans (PRSP) is poverty alleviation. This aim has been supported by the Millennium Development Goals (MDGs) from September 2000. The (MDGs) had eight core targets in total. The first of these goals are to eliminate extreme poverty and hunger. All of these goals were to be achieved by the end of 2015. All development partners want poor nations to make progress and improve in order to attain these goals. So, it is obvious that the (MDGs) are inseparably linked to the implementation of the Plans (PRRPs). Though, many nations have failed to attain the (MDGs) for poverty reduction. Surprisingly, poverty appeared to increase in certain Sub-Saharan African nations despite the fact that countries such as China, and Brazil, succeeded to lower income poverty levels (Benjamin, 2008).

There have been several Plans (PRSPs) assessments conducted to answer the issue of why the majority of low-income nations failed to properly implement their Poverty Reduction Strategy. Here are some of the reasons:

4.1.1. Reasons or Problems Concerning the Scope and Nature of Poverty Reduction Strategies

Gaps in poverty diagnosis: Gaps in poverty diagnosis: The Plans (PRSPs) was unable to be properly implemented due to insufficient or inaccurate poverty diagnosis. Poverty diagnosis is hampered by a lack of current data. Countries may diagnose poverty based on income rather than the factors of poverty. As a result, the Poverty Reduction Strategy Plans (PRSP) provided insufficient explanations for the poverty problem (Zuckerman et al., 2003).

Furthermore, poor poverty diagnosis resulted in inadequate information regarding gender, women's wages, and livelihoods in the Plans (PRSPs). As a result, the priorities, which are an important component of Poverty Reduction Strategy Plans (PRSPs), become unachievable (Whitehead, 2003).

Over optimistic growth projections: Overly optimistic growth projections: It is noted that the majority of the Plans (PRSPs) concentrated on promoting growth rather than complementing programs to eliminate structural poverty. Most countries' growth predictions for exports and financial income appear to be overly optimistic. Growth estimates are based on unrealized exports. There is also inadequate examination of the macroeconomic framework and structural improvements connected to poverty alleviation (Rafael & Lawson, 2005).

Poor treatment of governance concerns: For the Plans (PRSP) to be implemented successfully, openness, responsibility of public institutions, the rule of law, and government commitment are required. If a country's system does not adhere to good governance standards, poverty reduction targets may not be met (Dissanayake, 2013). Countries are working hard to modernize their justice systems, but progress has been gradual (Brautigam, 1996)

4.1.2. Challenges Related to Costing, Budgeting and Financial Management

To fulfill its intended aims, the Poverty Reduction Strategy Plans (PRSP) must prioritize resource allocation. This indicates that the government budget is extremely important in the implementation of the Plan (PRSP). As a result, governments must ensure that their poverty reduction strategy plans (PRSPs) reflect their budgets; otherwise, the government would be unable to properly implement the Poverty Reduction Plans (Levie, 2004).

Costs for the Plans (PRSPs): The Medium-Term Expenditure Framework (MTEF) enables impoverished nations to combine their national budgets and planning efforts. The (MTEF) is a planning instrument used to forecast resources for both domestic and externally funded projects. However, it is difficult to accurately estimate the Plans (PRSPs). This is because the (MTEF) is technically difficult and necessitates very trustworthy data. As a result, most impoverished nations' poverty reduction strategies fail owing to inadequate cost assessment (World Bank, 2004).

Weak relationship between the plans (PRSPs) and budgets: One of the issues that nations confront while developing and executing the (PRSP) is integrating the government's yearly budget with its medium-term expenditure plan. This makes prioritizing the Plans (PRSPs) difficult (Cheru, 2006)

Poor financial management and spending tracking: Effective execution of the Medium-Term spending Framework (MTEF) requires recording and monitoring of public expenditures. A sophisticated financial accounting system, as well as open budgeting and audits, are essential for an efficient monitoring and tracking process. In most impoverished nations, the budget system is inefficient and unreliable, with insufficient transparency to allow for easy and effective tracking and monitoring (UNECA, 2002).

4.1.3. The Challenge of Institutionalizing of the Participation Process

The participation approach distinguishes Poverty Reduction Strategy Plans (PRSP) from traditional development initiatives like Structural Adjustment initiatives (SAP). The involvement makes the Poverty Reduction Strategy Plan (PRSP) country-driven, unlike the Structural Adjustment Program, which was conditional and donor-driven and proven unsuccessful over time. Participation is supposed to create a sense of ownership, enhance policy creation, and ultimately lead to effective implementation. However, in certain underdeveloped nations, including local stakeholders is extremely difficult. In general, the participation procedure is not actual easy, and it is overseen by higher authorities (Sanchez & Cash, 2003).

Absence of true government commitment to the participatory process: The government's commitment to a participatory approach is critical for consultation and cooperative decision making (Painter, 2002). The government that permits individuals to participate in governance can effectively implement the Plans (PRSPs) (Eberlei, 2001). In certain poor nations, the participation process is not carried out properly. Consultations on the Plans (PRSP) are conducted in a haste without sufficient communication, particularly during the first stages of PRSP preparation (Whaites, 2002).

Limited involvement for legislative representatives: To achieve the national ownership aspect, the Plans (PRSPs) should include fully elected authorities. The participation of parliamentary members is critical because it allows parliament to promote accountability and openness in decision making. In many impoverished nations, parliamentary members and other high-level officials have not enthusiastically take part in the Plans (PRSP) process (UNCTAD, 2002).

Exclusion of the private sector: Exclusion of the private owned sectors: The private owned sector is crucial to development. Most governments do not include the private sector in the Plans (PRSP) process. Only a few developing nations actively participate in and communicate with the private sector during the Plan (PRSP) formulation process (World Bank, 2001). In most developing nations, organizations responsible for commerce such as the Chamber of Commerce and the Association of Manufacturers engage are consulted, but the informal private sector, such as women entrepreneurs, is not involved on a national scale (Eberlei, 2001).

4.1.4. Challenges in Meeting National Capacity Needs

Poor nations have national capacity issues while developing their own Poverty Reduction Strategy (PRSP). Most impoverished nations employ workers with little capabilities. A number of assessments have been undertaken in different countries, and the findings show that there is a considerable gap in the capacity to undertake poverty analysis, plan, implement, and monitor poverty reduction activities.(Cheru, 2006).

Poverty diagnosis and analysis: Most poor nations, particularly those in Africa, lack the human and institutional ability to conduct appropriate and systematic analyses in order to develop, execute, and monitor poverty reduction programs (Booth & Lucas, 2001). Furthermore, while poor countries do have competent workers with the skills needed for complex tasks such as evaluating poverty elements and poverty reduction strategy plans (PRSP), it is extremely difficult to retain and motivate skilled workers in most poor countries due to inadequate incentive schemes and structures in the civil service sector (Mick & Douglas, 2002).

Coordination and national ownership: Most impoverished nations experience poor coordination of economic policy initiatives while developing and executing the Poverty Reduction Strategies (PRSP). Most of the time, this occurs when there is an ongoing inter-ministerial disagreement about which ministry is accountable for a certain policy initiative, or when there is a conflict between sectoral ministries and ministry budgets (Cheru, 2006).

Poor monitoring and evaluation capacity is another difficulty that most low-income nations encounter, particularly during the implementation phase. This difficulty is mostly driven by a lack of technological capacity. Currently, most poor nations monitor and evaluate programs rather than focusing on the outcomes of poverty reduction policies and initiatives. Instead, they focus on closely adhering to government laws, regulations, and budgeting (Lucas et al., 2004).

4.1.5. Challenges Related to Harmonization of Development Partners Policies

Since the IMF and the WB developed the Plans (PRSP) idea, donor policies and practices have changed significantly (Booth & Lucas, 2001). Changes in development partners' practices might take the form of budget support or additional financing. In

Uganda and Tanzania, for example, development partnerships have shifted from stand-alone project aid to program aid and budget support (Koudougou, 2002)

Unpredictability in development funding from development partners: The time congruence between development partner policies and a country's Poverty Reduction Strategies is critical to a successful execution phase, mostly in terms of donor money predictability. The fact that most impoverished nations rely on uncertain financing from development partners has a damaging impact on the Plan's (PRSP) execution. It should be mentioned that most poor nations lack the financial flexibility to provide enough budgets for poverty reduction, therefore they rely on donor monies (Healey et al., 2000)

5. THE RELATIONSHIP BETWEEN THE POVERTY REDUCTION STRATEGY PLAN (PRSP) AND THE MDGS/SDGS

The United Nations Millennium Declaration was introduced during the United Nations Summit in held in 2000. This proclamation aims to coordinate worldwide efforts to eliminate extreme poverty. All international development partners and UN member countries agreed on this global approach, including its eight supporting goals (Woodbridge, 2015).

These objectives were presented as clear, quantifiable, and time-bound benchmarks that primarily focused on human development. Both poor and developed countries have promised to meet these objectives by 2015. To fulfill the MDGs, ten to twelve implications were necessary, followed by collective national policies, plans, and strategies backed by international initiatives. The underlying premise of the MDGs is to establish a goal-oriented international collaboration and local initiatives to assist low-income nations in eradicating poverty and promoting human capital development. It should be emphasized that the MDGs contained no answers for poverty reduction or human development (UNESCAP, 2015).

The Plans (PRSP) are the ones that give genuine plans for eradicating poverty, including financing, implementation, and monitoring frameworks. The Plan (PRSP) outlines the framework and tactics for achieving poverty eradication and other Millennium Development Goals. The Poverty Reduction Strategy Plan (PRSP) will be implemented over a longer period (three to five years). However, this execution duration is shorter than the Millennium Development Goals (MDG) implementation period, which was set at 15 years (UNESCAP, 2015).

Following the expiry of the MDGs in 2015, a new policy known as SDGs was implemented. The SDGs are intended to promote people, prosperity, peace, and partnerships. The SDGs are made up of 17 goals, 169 targets, and indicators. The Sustainable Development Goals not only aim to eradicate poverty, but also to promote international development and the preservation of human life. The SDGs are anticipated to guide all United Nations member nations' development goals and national policy preparations for the next 15 years, from 2015 to 2030. This means that, while the MDGs are exclusively applicable to developing nations, the Sustainable Development Goals apply to both developed and developing countries (Woodbridge, 2015).

5.1. Do the PRSPs Really Work on the Poor Countries?

Policy changes are done in developing countries in conditions that weaken impoverished nations' autonomy. Between 2000 and 2020, international organizations such as the IMF and the WB conducted a variety of reforms and development efforts in the majority of impoverished countries in Africa, Latin America, and Asia. Budgets, tax and spending policies, trade, tariffs, pricing, privatization, and credit policies are frequently linked to reforms and initiatives. Countries that carry out these adjustment programs often have less control over their economic policies and choices. This will have significant long-term consequences for recipient countries (Stewart & Wang, 2003).

Furthermore, it is believed that most impoverished nations construct their Poverty Reduction Strategies Plans (PRSP) in a rush due to a lack of time, resulting in biased plans that favor development partners in order to gain more financial support. Despite the fact that poor nations had varying economic levels, natural and financial resources, and government structures, their Poverty Reduction Strategies Plans (PRSP) often contained comparable economic ideas. This means that international financial institutions (IFIs) have influence on impoverished countries. This suggests that most of the plans (PRSPs) lack the sense of being owned by the government (Bartlett, 2011).

This is a difficult issue to answer since it relies on how the term "ownership" is perceived. The notion of ownership is difficult. The legal word "ownership" refers to private property of commodities or land. However, psychologically, it is interpreted as possession. When this phrase is employed in policy programs, the legal meaning is lost, and only the psychological meaning is used. The psychological meaning is based on human perceptions in such a way that governments, local people, and institutions are led to think they have ownership of poverty reduction strategies (Stewart & Wang, 2003).

According to the IMF and WB, the poverty reduction strategies should be led by countries or national governments. That is, the Poverty Reduction Strategies process and its contents should be produced in accordance with the notion of country ownership. This suggests that policies must be tailored to the local environment and capacity, as well as benefiting the country as a whole, rather than just external development partners (Adelakun, 2011)

Furthermore, in order to accomplish the notion of national ownership of Poverty Reduction Strategies, civil society engagement is viewed as necessary. To be country-driven and domestically owned, Poverty Reduction Strategies must incorporate wide engagement from civil society (Segura et al., 2004).

In many underdeveloped countries, the Poverty Reduction Strategies Plans (PRSP) system frequently restricts civil society participation in program formulation, giving governments disproportionate power. This is due to parallels between PRSP and other Structural Adjustment Programs, with few procedural differences. As a result, PRSP methods have limited relevance to most International Financial Institution operations, reducing their effectiveness in empowering impoverished nations (Stewart & Wang, 2003).

5.2. CONCLUSION

Basically, it can be concluded that these strategic plans somehow help developing countries, as progress is noticed from year to year despite the fact that most of the objectives and goals of the plans are partially achieved. This may be due to the unmet conditions that delay the application of the programs and projects to the plans.

It also may be concluded that, though the preparations of the papers and plans are said to be inclusive and country-oriented, it is undeniable that most of the programs and projects that are included in them are externally influenced. This influence may not be a direct influence, but the fact that plans are funded externally with conditions attached to them is enough evidence of being externally influenced. With this fact being said, the feature of these plans being country-owned and oriented may be in question.

There has been noticeable improvement in procedures and processes to prepare strategic poverty reduction plans in most countries, but the question may be whether the wide participation and inputs of the stakeholders are considered or not. Following the wide participation procedures is one thing, but considering the inputs gained from the stakeholders in the process is another. At this point, the responsible institutions in the preparatory phase, instead of focusing on how wide the preparation process was, should focus on how efficient the process was by accepting the inputs gained and adopted from the stakeholders.

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THE IMPACT OF BOARD GENDER DIVERSITY ON ENVIRONMENTAL SUSTAINABILITY

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ABSTRACT

Purpose- The Board of Diversity helps companies make more democratic and correct management decisions. The contributions of gender diversity to the financial and non-financial activities of companies are significant. This research was conducted to show the positive contribution of women executives to the environment.
Methodology- The study sample includes 108 American companies in the S&P500 index. The study was organized with panel data of USA companies between 2008 and 2021. OLS regression method was used to analyse the results.
Findings- According to the results of the analyses, the environmental impact of women on the company board is positive and significant.
Conclusion- This study figures out that women executives have higher sensitivity and responsibility towards the environment than men. According to these results, it is essential both in terms of dealing with global warming and in terms of achieving the UN's 2030 targets.

Keywords: Sustainability, board diversity, gender diversity, environment, woman on board, ESG.
JEL Codes: G30, G34, M14

1. INTRODUCTION

Global warming continues to be one of the most critical problems in the world. However, the United Nations has announced a zero-carbon target for 2030. The United Nations (UN) has set 17 Sustainable Development Goals to achieve this goal. Among these goals, "SDG 5 Gender Equality" and "SDG 10 Reducing Inequalities" are of great importance in achieving sustainability goals. In particular, the elimination of inequalities based on gender is necessary to eliminate gender discrimination.

Unfortunately, the gender imbalance in society persists in business life. Sustainable development will only be possible if countries and companies adopt all these goals simultaneously (Özparlak et al., 2023). Today, women are knowledgeable, educated, and qualified enough to do almost as many jobs as men can. However, imbalances in the labor force are also seen in corporate business life. Social and institutional equality is also a requirement of the rule of law and fundamental rights (Özparlak et al., 2022). Currently, the proportion of women executives (WOB) in the management of companies does not even correspond to half of the proportion of male executives.

However, the board of directors (BOD) is the most critical part of a company, where decisions and strategies are determined (Adams et al., 2015; Özparlak et al., 2023). The board of directors' characteristics, such as gender, age, tenure, and race, are examples of diversity (Harjoto et al., 2015). Ensuring diversity in the board of directors is also crucial in gaining different perspectives and strengthening the representation authority of the board. Ensuring diversity in the board of directors also plays a vital role in increasing the performance of companies.

Increasing diversity in the board of directors and its effects is one of the most studied topics by researchers recently (Nowell et al., 1994; Erhardt et al., 2003; Campbell et al., 2008; Nadeem et al., 2019, Nadeem et al., 2020; Özparlak et al., 2023; Gürol et al., 2023). In particular, many studies on gender-based diversity (Gürol et al., 2023; Özparlak et al., 2023). In the literature, many studies show that the company's financial performance improves with women in management (Nowell et al., 1994; Campbell et al., 2008). Nadeem et al., 2020). Women's different perspectives, high communication skills, and detailed work increase the financial performance of companies. In addition, women are more sensitive to the environment than men (Dhenge et al., 2022). The increase in the number of women in management contributes positively to the environmental sensitivity of companies (Gürol et al., 2023). However, some literature studies have found that the contribution of women managers to the environment is negative (Cucari et al., 2018).

This study was conducted to contribute to this dilemma in the literature. This study has been conducted to show the positive contributions of women on the board (WOB) to the environment (E). The study is recommended to researchers and policymakers in the policy maker section. In this way, it is aimed to contribute to the sustainability goals of the United Nations (UN). The study is essential in dealing with global warming and accelerating sustainability goals.

The data set of the study was obtained from Bloomberg Data Terminal. Bloomberg categorizes the sustainability scores of companies under three main headings. Environmental (E) value shows the environmental scores of the companies. Social (S) scores companies' sensitivity to social issues. In addition, Governance (G) scores companies' governance activities. The arithmetic average of these three scores gives the companies' sustainability (ESG) scores.

Some studies in the literature have examined the relationship between board diversity (BOD) and ESG scores. However, since some of the (S) and (G) scores are already derived from board diversity variables, analyzing this relationship may be both semantically and statistically flawed (Özparlak et al., 2023). Therefore, this study examines the relationship between the proportion of women on board (WOB) and companies' environmental (E) sustainability scores. The study sample consists of 108 USA companies from the S&P500 index for which data are available.

Panel data and OLS regression were used as a method in the study. According to the study results, WOB contributes positively to companies' environmental scores. Moreover, this study makes two significant contributions to the literature. Firstly, the positive contribution of gender diversity to the environment is demonstrated. Secondly, there is still a dilemma in the literature on the contribution of women to the environment. This study contributes to the literature by proving the positive contribution of WOB. WOB ratios are one of the most fundamental variables of BOD. The validity of this variable is also essential for the validity of BOD.

In the second section of the study, literature studies are mentioned. The third section mentions the data and methodology used in the research. In the fourth section, research results are shared. The fifth section discusses the results and recommendations for policymakers and researchers.

2. LITERATURE REVIEW

According to the resource dependence theory, increasing diversity in the board raises the company's access to different resources (Hillman et al., 2000). It is because directors of different genders, different cultures, and different minority groups on the board of directors can act as a bridge in the company's connection with different societies, different cultures, and different resources. Because women are more assertive in communication issues, they can cause the company to obtain maximum benefit from different resources. Companies can leverage women's skills and beliefs to develop more effective and sustainable environmental policies, considering many circumstances. These characteristics of women can increase environmental performance and companies' green reputation. Thus, the profitability of companies can increase. In this case, ensuring BOD is essential for a company's financial performance and prestige.

There are many studies in the literature state that the positive relationship between the WOB and the financial performance and market value of the company (Nowell et al., 1994; Campbell et al., 2008; Erhardt et al., 2003; Reguera-Alvarado et al., 2017; Nadeem et al., 2019; Wilson et al., 2009). A balance between board gender diversity is essential in making more innovative, creative, and better-quality decisions (Wellalage et al., 2013). In addition, men's and women's different perspectives and experiences on issues can facilitate the company's decision-making processes. The presence of female employees can enhance team performance because more diverse teams can lead to a broader perspective and, therefore, better decisions can be made. These decisions can ultimately lead to higher job satisfaction and productivity (Burgess et al., 2002).

Communication can also be expressed as transferring feelings, thoughts, opinions, or information between people. Communication can be carried out verbally and by transferring feelings and thoughts in writing. Considering that women are more effective than men in terms of communication in business life, we can also understand that they interact more effectively with other employees in the company. Thus, in a crisis, this communication can lead to positive interaction and motivation to overcome the crisis. However, management in times of crisis will also be with the success of female managers or employees. If we consider the characteristics of women, such as interpersonal relationships, empathy, social responsibility, self-esteem, and stress resistance, a woman in any position will make a difference in the place where she works because of these characteristics. In the past, men could hold higher positions because of their stress resistance. However, now that people's skills are more important, women's improved interpersonal skills will enable them to reach higher positions (Dr Steiner et. al). In addition, studies explain women's positive environmental performance on the board (Özparlak et al., 2023; Gurol et al., 2023; Nadeem et al., 2020). Women are much more sensitive to the environment than men (Dhenge et al., 2022). Women are different from men in terms of their sensitivity to the environment and looking after other people's interests (Carlson, 1972). Female managers are more caring and kinder towards the environment (Eagly et al., 2003).

The contribution of female employees is outstanding, especially in recycling and more economical use of internal resources. Again, we can associate this situation with the more giving and sensitive nature of being a woman. Women have feminine characteristics and are more sensitive to their maternal structure. It is in women's nature to be more embracing and thoughtful regarding being more sensitive to the environment. If we talk about the sense of justice, since the emotional structure of women is more prominent, their sense of justice has also developed. This situation shows us that women who are managers behave more justly to their colleagues working at lower levels. If a company has an environment of justice, trust, and motivation, employees who are more sensitive to the environment and the company motto can also be created. A feminine company is a sensitive company, embracing and having aesthetic concerns. Aesthetic concerns are inspired by nature. An organization inspired by nature will be more sensitive to the environment.

In the future, aesthetics will be an essential issue for companies. The only way to achieve this is to look like a woman. If we reach the natural in the perfect by taking our inspiration from nature and returning to nature again, we can be more sensitive to the environment.

From another perspective, the woman-nature relationship can be represented by metaphorical expressions such as "Mother Nature" (Guthrie, 1993). "Mother Nature" is a common personification that focuses on nature's life-giving and nurturing aspects, embodying it as a mother (Jelinski, 2011). Here, in fact, with the definition of mother, we can see the woman's relationship with nature and the woman's contribution to nature through this transformation.

With these perspectives in mind, companies can capitalize on women's innate skills and beliefs to develop more effective and sustainable environmental policies, improving environmental performance and enhancing companies' green reputation, thus increasing profits.

In light of these studies in the literature, the following hypothesis is proposed in this study.

H_1: The Woman on Board (WOB) is positively associated with Environment (E) scores of the companies.

3. DATA AND METHODOLOGY

3.1. Data

In the study, companies in the S&P500 index in the USA were taken as a sample. The data of 108 companies in the sample between 2008 and 2021 were accessed.

Table 1: Definition of Variables

Variable	Symbol	Source
Environment Score	E	Bloomberg
Woman on Board (%)	WOB	Bloomberg
Board Size	BS	Bloomberg
Financial Leverage	FNL	Bloomberg
Tobin Q	TQ	Bloomberg
Total Assets	TA	Bloomberg

Table 1 shows the definition of the research. The data was provided from the Bloomberg data terminal. The environmental scores of the companies calculated by Bloomberg are indicated by (E). Bloomberg calculates sustainability scores by measuring many factors and their effects. Environmental scores take a value between "0" and "100". The WOB ratio shows the percentage of women on board. It is calculated by dividing the number of women on board by the number of people on board (BS). Board Size (BS) explains the number of company boards. Financial Leverage (FNL) is a financial indicator used to show companies' risk status. It is calculated by dividing the Total Debt ratio by the Shareholder's Equity value. Tobin's Q (TQ) is another indicator used as a performance measure of companies. In addition, it gives the market value of a company. This ratio is obtained by dividing the market value of the financial rights of the firm by the current replacement cost of the firm's assets (Nguyen et al., 2015). Total Assets (TA) shows the total assets owned by the company. This value is an indicator value to show the size of companies. In the study, the logarithmic transformation of the TA value was made.

Table 2: Definition of Company Sectors

Bloomberg Sectors	Number of Company
Financials	18
Industrials	16
Utilities	14
Materials	13
Consumer Staples	11
Health Care	10
Consumer Discretionary	8

Information Technology	8
Energy	4
Communication Services	3
Real-Estate	3
Total	108

Table 2 shows the distribution of companies in the sectors. Accordingly, the most common sector in the study is the finance sector (18 companies) and the least common sector (3 companies) is the real state sector.

Table 3: Definition of Company Size

Size of The Company	Total Asset ($)	Number of Company	Number of Company (%)
Large Size	5 million - 1 million	37	34.3%
Medium Size	100 thousands -10 thousands	61	56.5%
Small Size	10 thousands - 0	10	9.3%

Table 3 shows the distribution of the companies according to their size. According to these results, 37 companies are in the large size group. It equals the %34.3 of all companies. In addition, there are 31 companies in the medium size group. It corresponds to %56.5 of all companies. The number of companies in the small size group is 10. It corresponds % to 9.3 of all companies. Accordingly, the sample's most significant number of companies belongs to medium-sized companies, with 61 companies. In addition, the small group has the lowest number of companies, with 10.

3.2. Methodology

Panel data is used in the study. OLS regression model is used to test our hypothesis H_1. The model is specified as follows:

$$(E)_{it} = \beta_0 + \beta_1.WOB + \beta_2.BS + \beta_5.FNL + \beta_6.TQ + \beta_7.TA + \mathcal{E}_{it} \quad (1)$$

In equation (1), E is the dependent variable. (*i*) represents companies and (*t*) represents years. WOB is the independent variable. BS, FNL, TQ and TA are the control variables of the study. Ɛ is the error term of the equation.

4. FINDINGS

4.1. Descriptive Statistics and Correlation Analysis

Figure 1 shows the E, S, and G scores of The USA Companies between 2008 and 2021. According to the results in figure 1, all three scores are in an upward trend. It is seen that these three sustainability scores (E, S, G) are in an upward trend. The fact that these three scores are increasing is precious in achieving the UN's sustainability goals. Nevertheless, whether it is sufficient is a separate issue that needs to be discussed.

Figure 1: Average E, S and G Scores of the Companies

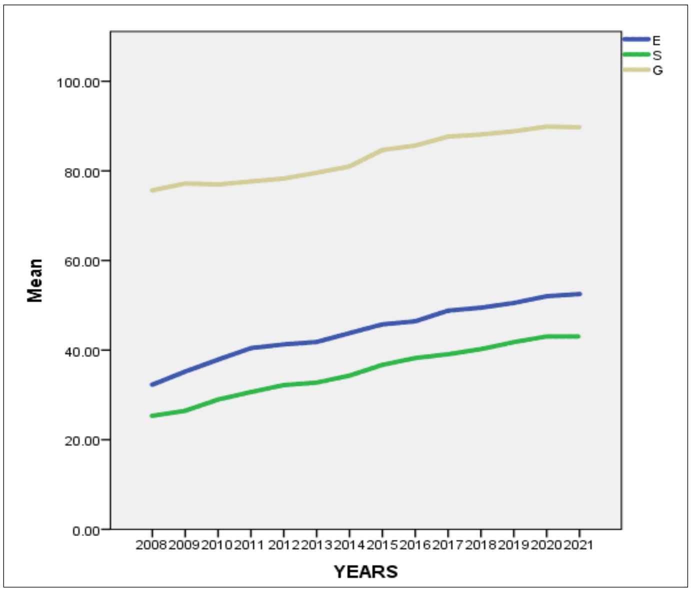

Figure 2 shows the number of WOB in US companies between 2008 and 2021. Looking at the graph, the number of female managers in 2008 was approximately two people, which increased to 4 in 2021.

Figure 2: Average Number of the Woman on Board in the Sample

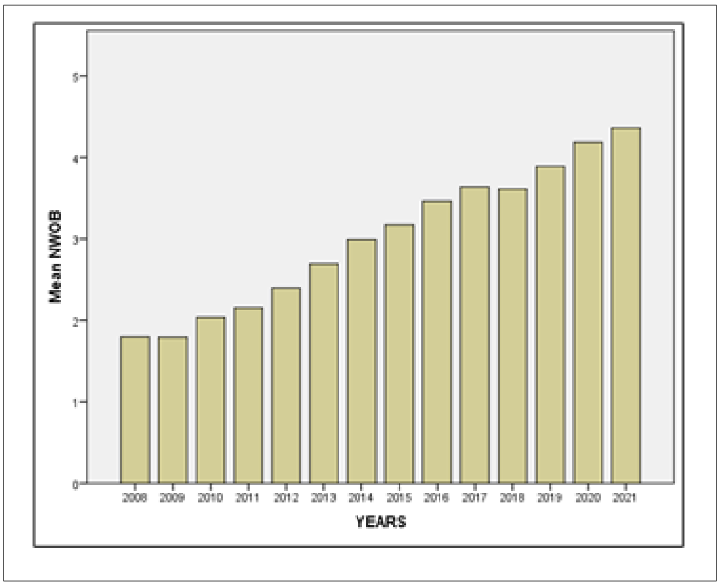

Figure 3 shows the percentage WOB of the USA companies between 2008 and 2021. This ratio is calculated by dividing the number of women on board by the number of people on the board (BS). Therefore, the result is expressed as a percentage (%WOB). In 2008, the WOB rate was 15 percent; in 2021, this rate increased to 37 percent. Compared to 2008, this rate has more than doubled. It is a positive result to achieve an increase in this rate due to legal obligations and sustainability pressures. However, the presence of WOB without or with limited authority makes them a puppet representative.

Figure 3: Average Percentage of the Woman on Board (WOB) in the Sample

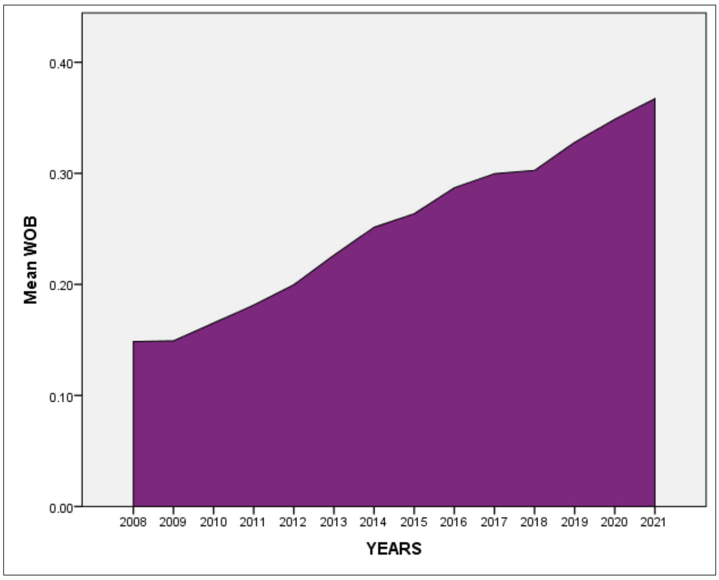

Table 4 includes the descriptive statistics of the study data. There are 1512 values in the panel data sample. FNL is the value with the highest maximum value. E is the variable with the highest E value. E, WOB, and TQ are the variables with zero value and the lowest value.

Table 4: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
E	1512	0.00	84.42	44.160	16.378
WOB	1512	0.00	.70	0.251	0.128
BS	1512	5.00	25.00	12.093	3.248
FNL	1512	1.27	1601.25	7.626	42.260
TQ	1512	0.00	16.26	1.762	1.458
TA	1512	2.81	6.50	4.654	0.712

Table 5 shows the results of the correlation analysis of the research. There is a positive and significant correlation between WOB values and E values of the companies. The results are consistency with literature studies (Özparlak et al., 2023; Gurol et al., 2023)

Table 5: Correlation Matrix

	E	FOB	BS	FNL	TQ	TA
E	1	0.101 **	0.085 **	-.020	0.060 *	-.039
WOB	0.101 **	1	-0.073 **	-.017	0.091 **	.119 **
BS	0.085 **	-0.073 **	1	.013	-0.209 **	.441 **
FNL	-0.020	-0.017	0.013	1	0.013	.051 *
TQ	0.060 *	0.091 **	-0.209 **	.013	1	-.324 **
TA	-0.039	0.119 **	0.441 **	.051 *	-0.324 **	1

Note: ***, **, and * denotes significance level of 1%, 5% and 10% respectively.

Table 6 shows the OLS regression test results of the study. R^2 is %3.1, and the model's F statistic value is significant (*p<0.05*). According to these results, the effect of WOB ratios on E is positive and significant. These results are consistent with the literature studies (Özparlak et al., 2023; Gürol et al., 2023). In addition, the effect of BS on E is also positive and significant. On the other hand, the effect of FNL and TA control variables is negative and statistically insignificant. The effect of TQ on E is positive and statistically insignificant as well.

Table 6: Result of OLS Regression

Depended Variable: E		
OLS Regresion		
	B	***t-statics***
Constant	42.083	4.713 ***
Independent Variables		
WOB	14.891	1.951*
Control Variables		
BS	0.747	1.704*
FNL	-0.005	-0.401
TQ	0.452	0.653
TA	-2.443	-1.296
R^2		0.031
Adjusted R^2		0.027
F-Statistic		9.500
Prob.		0.000

Note: ***, **, and * denotes significance level of 1%, 5% and 10% respectively.

5. CONCLUSION

This research focuses on board gender diversity. The study aims to contribute to the United Nations (UN) 2030 sustainability goals. In particular, this study refers to targets 5 (Gender Equality) and SDG-10 (Reduced Inequalities). Gender equality and reduced inequalities are not only an obligation but also a requirement of the Universal Declaration of Human Rights. However, these goals are essential not only for individuals but also for companies. Equality between the genders in business life must also be ensured.

In this context, the boards of directors of companies are essential. Because the decisions made there affect all employees and, indirectly, the whole of society, the BOD can ensure that the decisions made by the board of directors are correct and democratic. BOD can be ensured by differentiating variables such as race, gender, age, and length of service.

One of the most important independent variables in the BOD is gender diversity. However, when female executives are mandatorily appointed (Burgess et al., 2002) and are not empowered, they should not be expected to be effective on the board. However, when empowered, female executives are more sensitive to social issues than male managers (Birindelli et al., 2018). However, studies have generally focused on WOB ratios and company financial performance or financial risk. The number of studies focusing on non-financial issues is minimal. This study focuses on the relationship between WOB and companies' e-scores. For the research sample, 108 USA companies were analyzed over 14 years. It is tough to obtain companies' sustainability scores. Therefore, the study has limitations. The research covers 108 companies in the S&P500 for which data is available. The main reason for selecting the S&P500 companies in the study is that the companies in the S&P500 should be corporate firms that are among the largest companies in the USA and the world. It increases the confidence in the data set. In addition, the data could be accessed due to their proximity to the sustainability concepts.

According to the results, the WOB ratio's contribution to the companies' E-scores is positive and significant. These results exemplify that women can be successful executives when they are removed from being dummy managers and given authorizations appropriate to their education and experience. In addition, it has been proved that women executives can be more successful in social, organizational, and managerial areas rather than only managing the financial performance of companies.

Concerns about global warming are increasing day by day. The damage caused by humanity to nature must be stopped as soon as possible. For this, businesses must first be at the forefront of these efforts. The decisions taken by the enterprises' boards of directors have a critical value in this sense. In this sense, policymakers need to apply the necessary incentives and sanctions to ensure that the decisions made by the board of directors of companies align with sustainability targets.

Apart from this, training should be organized to improve sustainability and to ensure that the employees understand it well. Companies with high sustainability scores should be incentivized and given some privileges. Efforts should be made to increase the diversity of company boards of directors.

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COMPETITION LEVEL ANALYSIS FOR THE FINTECH SECTOR IN TURKIYE COMPARED TO GERMANY

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ABSTRACT

Purpose- This study's objective is to observe Türkiye's fintech market structure by their competitiveness results. To get a better observation Türkiye compared with a fintech-developed country as Germany. The inconvenient definition of fintech caused this study to examine 4 massive fin-tech sectors. Especially current situation of the financial-technology market there are several branches. The study refrains from the engineering-intensive branches to serve its purpose. The study includes; Payments, Lending, Personal Finance, and Insuretech branches. We expect to observe the competitive dynamics for several branches.

Methodology- The study selected the "entropy index" as a method. The entropy index shows the market depth for related sectors. It can be defined as a density analysis. We can make the index with at least 5 observations. However, the increase in the observation level causes the low-variance level index results.

Findings- The study made its index by the top ten firms by their sales revenue level. The study observes the market in 5 branches. The conclusion part supplied 5 different density results. In that situation, observations can be seen more specifically for the market. The study used the entropy density index to observe the competitiveness level of the market. Results were multiple because the branches were divided from the sector. Every branch has its dynamics. On the Türkiye side, we expect fewer companies than in Germany. However, in the personal finance sector, we can observe the competitiveness levels are close. However, in this study, we can also observe high gaps between the sectors of insurance tech and lending. This study did not have the purpose of determining the factors behind them but the study tried to give political suggestions.

Conclusion- The density level for lending and personal finance sectors can be compatible with a high-fintech level company. For the insure-tech side, companies value and numbers are lower. The payment sector has more technology than the other sectors but the number of firms are lower than in Germany. We were expecting the competitive structure are not improve in Turkey because of the low-quantity firms. At some branches, we obtained the results that support this expectation. However, the view of the study observed that some branches has low competitive market structure when compared the Germany. But at some points, there are massive cliffs between the two countries. We can attribute the situation to the habits. The habits of technology meant. Especially on the insurance side, Turkey should improve itself. Türkiye should be getting more investment, subsidies, etc. in the sector of insure-tech and payment sector. Because their competition level is a risk to the country's market structure. This study includes no detailed politics but suggests to subsidies and incentives from the government side. Government should support and encourage the new-entry firms or entrepreneurs for the sector of fintech.

Keywords: Fintech, fintech demand, fintech factors, tech fin, technological progress, behavior finance
JEL Codes: F65, G15, G22, L11, L22

1. CONCEPTIONAL FRAMEWORK OF FINTECH

At the anthropocene age technology had the incrediably motion shiftwards. That technology affects the real sector which, industry, aggriculture, services sectors etc.. After the affections for real sector, financial tools has affected for after all that technology. Evolution says the weaks eliminate by strongs. This elimination for economy is clearly technology. When this technology combine with financial services, fintech borns. Making traditional banking/finance services with maximum technology named fintech. Fintech is a combination not an invention for humanity. That combination has gave humanity a comfort that no century gives for a thousand years. (Schueffel, 2016, p.1-23)

1.1. Sector of Fintech's Structure

When the introduction occured between the sector of finance and technology so many branches has borned. Each fractions have a different purpose and service capability for the demand side of the sector. As a structural change we can observe both traditional and financial technology sector has similar obligations with eachother. As a services perspective we come across with; digital banking, mobile banking, payment services, digital currencies and coins, wealth and assets managements and cosultants, personalized financial consultans, technological insurence services (known as Insure tech) and innovation firms that creating new Technologies for financial services by R&D process (known as TechFin firms). However we still can't have a point of idea about financial technology branches. Evolution's destruction effect creates and demolishes some sector at the same time. As a conclusion we can say the sector of fintech has a rapid growth and structure. (Schueffel, 2016, p.1-23).

1.2. Fintech Sectors Included in this Research

Taking the all branches and co-sectors for fintech as a base for this study can give us a confusing conclusions. Study pays attention the branches with their different financial tools. Branches that have more technological improvment can be more seductive for the individuals. On the another perspective behavioural finance pushed this study into these sectors. To make a categorize we can have digital banking and payment sector as a services factor. Because payment services spread all the society base for the innovation against traditional payment systems. Personal finance as a management to managing our portfolio. Lastly it has to be security factor for insuretechs. From the origin of humanity, security is always the physiological factor for us. To sum up his Study includes; Digital banking, Payment services, Personal Finance, Insuretech as a base. We can obtain with each sector for a individual behaviours against the sector of financial technology.

1.3. Fintech for Today

Fintech has a complicated chronological history. We can't be sure about the origin of fintech. In the 18th century, telegrams were the most technological factor in the technological finance ruritanian. After the mobile finance, we can divide the rooms for two. Because 19th-century's mobile banking and millennium mobile banking have different motions and structures for each other. However, today has a different technological context in a way unlike any other time. Especially after the Covid-19 crisis, technological finance systems gained society's perception. Perception has an enormous importance for the sector of finance and also the financial technology systems. Both sector know their customers as deposits. (Boot, et al., 2021)

Many studies have tried to classify the history of fintech and many historical joints have been mentioned on this subject. Interoceanic cables, which were laid towards the end of the 19th century to facilitate communication and transfers between countries, can be considered as the starting point of technology for the financial system. Swift systems, which provide online banking and foreign exchange exchange opportunities all over the world, have opened a new era in digital banking. Today, financial technology systems help provide enormous convenience to customers by restructuring traditional banking products with high technology. In today's finance, customer movements and behaviors can now be managed and observed much more easily. This makes serious contributions to the literature of schools such as behavioral finance. (Çalışkan,2021)

2. LITERATURE REVIEW

Finance sector adapted the technological improvement more easily than other sectors. On that perspective financial growth rates can be enormous sometimes. To easier the traditional banking services gave the fintech sector more optimization and productivity on the both demand and supply side. However fintechs can be into a hard situation when entering the market sometimes. Such as Traditional Banks that merging with tech firms (Lestari and Rahmanto, 2021). On the global market fintech sector has adjusted 306 billion dollars share (Katılım finans, 16.01.2024). On the Türkiye's perspective, technology of fintech and the perception of the society had a delay when we compare with other countries. Concept of fintech includes some sector in Türkiye such as; Digital payment services, insurances, mobile banking etc. to build an effective market. In 2023's annual reports Türkiye has 1,6 billion dollars investing volume for startups or board firms already. That annual values, put the Türkiye 10th place in the Europe scale. (Turkish Presidential Finance Office, 2023) Also on the another perspective Türkiye has about 0,30 growth rate as a whole sector. That number can be understandable if we noticed Solow's growth model due to the transaction dynamics. On Germany's sector perspective of fintech, the country has a enormous investing rate. Germany has lots of R&D and intelligent intensive labor fort his sector. Technology has almost perfectly place in the country with digital payment habits that spreaded along the citizens with a non-discriminate age scale. Also Germany has the 3rd place for almost 11 billion dollar fintech investment rates compare with all of Europe. The country has plenty of unicorns and decacorns itself. (Turkish Presidential Finance Office, 2023)

The study delves into the behaviours from 102 participants with their several level of financial literature levels. Study calculates their fintech using ability for each participants. Study found that, financial technology sector is understandable but the sector needs more training and educational system to spread the fintech tools to the society-base. Another perspective from the study is the competition level for countries. If we have a cumulative road from society to the country, we can say, countries that have less financial tools (technological) literature level or less trainings will be doomed to become a underdeveloped country in the competition enviroment (Fettahoğlu and Kıldıze, 2019)

The Academical Study aims to infrastructures to make an appropriate using the financial tools along the countries. Infrastructure factor can be a barrier for competition level of between financial technology firms. As a perspective of the countries, infrastructures can affect the using-knowledge of financial technology tools for the citizens. Countries that have a low level of infrastructure for the fintech creates a low endowment for financial technology ability to use (Bilgel and Aksoy, 2019).

Obverves the creation in the financial technology sector called as inovation. The inovations create a depth that influence the demand and supply variables. This influence competition noticed by firms that want to be a best selection in their sector. That article listed the factors that affect the both supply and demand sides. Some government policies which can be counted as regulations, also some cultural demographic structures affect the demand side of fintechs. At the supply side perspective changes in financial or macroeconomic fundamentals, technology based growth has a affection of supply (Schindler ,2017).

The parliament study observes and reports the competition level in the financial technology sector. Study obtains 7 co-sector as a branches of financiial technology. After the classification those 7 sector has taken as a fundamental of the competition analysis. This analysis report has a key Word that “change”. Changing in the infrastructure and economical fundamental affects in three way as; new technology is changing the system of services completely, new technology is changing the demand side as financial tools users, new technology is changing the way of how the financial services will supply? (Competition issues in the Area of FinTech, European Parliment Report Archive, 2018)

In this study financial Technologies are discussed as a government perspective and European Regulations. As a context of PSD2 directive that creates by the European Council to regulate the payment services observe as a barrier. We can observe that government contributions to make the sector of fintech more controllable and obeyfull for the country's benefits count as a factor that decreases the competition level (Vezosso, 2018).

The study, financial technology sector’s competition level analyze by the perspective of regulations and government policies. If we have a spesific part of the study we can accept the government policies as a positive externalities. Government regulations help the sector of banking to spread their risks. In that way banking and its technological branch can be supported by regulations (Milne ,2019).

This study supply a chronologic cumulative history about financial technology. When financial technology development occurs there are some new competition factors about the sector. Increasing technology in fintech causes a more fierce competition enviroment for the firms. This development in the technology keeps the companies stay on their toes. Also in this study includes that technology provides the firms to make a new aggrements with different sectors. In this way banking systems and businesses become more relatively with eachother (Körpe ,2021).

Study includes two different dynamics in the sector of finance in a perspective of sustainability. Those different Dynamics can’t be comperabe with eacother by competition indexes. Financial technology services has a growing scheme includes technology. In that way when the technological develation occurs, there is a new services in financial technology. Within a extreme situations traditional bankings can’t be a securefull systems to the citizens. However fintech industries in the extreme situations can be hacked by international hackers. If we contains a merging between tradtional and fintech sectors. We can observe the traditional banks are merging with financial technology services to create a sustainable path (Suprun et al., 2020).

In this study we can observe a different perspective in the financial technology services’ competition level can be determine by the innovation sector from outside the finance sector. When there is a growth in technological innovation sectors by creating a less comperativity causes a increasing the market gap as a financial technology institutions. We can accept the special patents in services sector as a factor creates a cliff between the sectors (Caragea et al., 2023).

This study taken China as a base. Countries like china have a enormous population and labor intensive come across with a diffiicult financial system. Creating and producing technology related to fintech can be a liberization path instead of the traditional banking system. Study obtains a perspective from both individuals structure and the firms with making progress with banks. Both side prefers the fintech competitors instead of traditional banking product and services. That causes to move the competition platform only for a one sector called fintechs (Buchak et al., 2021).

There is a disinformation about the definitions of fin-tech and digital banking. Digital banking is more like the sectoral phenomenon. This study aims the effect of fintech integration process to the digital banking and consumer demand side. The study includes some countries to observe the effects. In conclusion increased financial services due to the fintech integration creates more competitive enviroment for the sector of fintech. (Aloulou et al., 2024)

At some studies, we can observe the effect of AI in competition terms. AI has a massive position in the finance sector. After some interdisciplinary performance between finance, engineering and economics fintech was born. In the current situation of the market, the AI level may affect the competition level for the sector. AI should be adopted in all sectors, however at some industries or sectors AI has a more attractive perpective than the others. Finance is one of those sectors. AI services, chatbots, personalized finance with risk management have a serious affect to stand out among other companies. Services of the finance sector should be more privately and special advice, AI will make it happen. After that it will change the competition equilibrium in the market. (Agrawal,2024)

3. ANALYSIS OF FINTECH COMPETITION LEVEL

The table 1 includes both Türkiye and Germany's fintech companies listed in 4 sectors. Company's are listed for their market share for each sector). Also there are fintech firms from Türkiye in the table 1. We included the firms that build their firms in a based from in their countries for overwhelming majority in some cases. But there are some special cases too like some payments fintechs in Germany. As an example Previse is not a Germany-based firm but it has a great trade volume that we can't side eye in the country. In that way we can describe the firms as "have an important sales revenue number in the country".

Table 1: Fintech Firms Both Global and Türkiye

LENDING FIRMS	PAYMENT FIRMS	PERSONAL FINANCE FIRMS	INSURETECHS
AuxMoney	SumUp	Trumid Financial	Clark
N26	Previse	Tink	Coya
SolarisBank	PayWorks	Yodlee	OttoNova
Raisin	Shopkick	Gravity Payments	Friendsurance
Finleap	İyzico	Clinc	Sigortam.net
Mambu	PayCore	Parasut	egaranti
Papara	Ininal	FigoPara	Wyseye
Tarfin	Paym.es	KolayBi	Fonradar
MobileExpress	Pozitron	ManiBux	SmartIR
Figopara		Finmaks	
Beemo		Lumnion	

Lending for decentralized finance is one of the key instruments for the financial technology firms. In this study I used the fintech firms have a bigger portion for lending services than other instruments. We take the numbers from several sources such as company balances, public interviews etc. Those number show us a how much revenue did the company get this year from their lending services. Biggest volume in this table belongs to N26. Second is the Mambu for about 104 million dollars ($). Auxmoney is the another lending fintech from the Germany had about 54 million dollar revenue from the lending services. Solaris Bank on the 4th part of the table as a sales volume. "Raisin is another fintech lending firm from Berlin. On the last firm is Finleap from another Berlin-based fintech company that has a revenue of about 25 million dollars ($).

Table 2: Lending Firms' Sales Revenue in Germany

LENDING FIRMS	Sales Revenue ($)
AuxMoney	53.800.000
N26	300.000.000
SolarisBank	38.000.000
Raisin	28.600.000
Finleap	24.800.000
Mambu	104.100.000

Papara is the biggest lending fintech in Turkey and has a enormous sales value when we compare the firms with each other. Second firm is the Tarfin. Tarfin make lending operations but their aim customer profile is the customers in the aggriculture sector. Tarfin has offices almost every city in Türkiye. Rest of the three financial technology firms have almost the same value between each other. But their volumes are so low to be compete

Table 3: Lending Firms' Sales Revenue in Türkiye

LENDING FIRMS	Sales Revenue
Papara	28.600.000
Tarfin	17.300.000
MobileExpress	2.200.000
Figopara	2.000.000
Beemo	2.000.000

Mention to the description under Table 1. We have some non-domestic firms in Table 3 but the firms are great value fort he result we looking for. SumUp has an enormous value if we compare with other firms in payment sector. On the second place there is a Danish fintech firm Previse with 35,3 million dollars sales revenue. Another non-domestic firm Payworks (U.S.) is on the 3rd place with 27,6 million dollars revenue. Last firm is Shopkick with 24,2 million dollars in revenue. On the Türkiye side, Iyzico is the biggest payment firm in the sector with a revenue value of 51 million dolar Paycore with 20,3 million dollars in revenue has a second place. Ininal is another financial technology firm in payment services. The last two firms in Table 3 have a depreciate value when we compare them with other firms. The last one is Pozitron which is also another payment services firm in Türkiye.

Table 4: Payment Firms in Türkiye and Germany

PAYMENT FIRMS	Sales Revenue	PAYMENT FIRMS	Sales Revenue
SumUp	159.000.000	İyzico	51.000.000
Previse	35.300.000	PayCore	20.300.000
PayWorks	27.660.000	Ininal	13.500.000
Shopkick	24.200.000	Paym.es	3.300.000
		Pozitron	1.500.000

Personal finance is the evolve of the technology and traditional banking counter system. In this sector we can have special investment reccomendations, portfolio management etc. In this sector the biggest value in Germany is Tink AB with 157 million dollars ($). On the second place belongs to Yodlee. Gravity Payments is on the 3rd place with 69,1 million dollars ($). Clinc with 59,7 million dolars sales revenue. Lastly there is a personal finance services firm named “Trumid Financial” with 33,3 million dollars ($). On the other side Türkiye has some fintech firms have personal finance services for their customers. But in Türkiye there are some nominal firm advantages on the perspective of “Parasut”. Parasut on the first place with 15,6 million dollars ($). FigoPara and Finmaks in their table with almost equal shares. Lumnion with 3,5 million dollars sales revenue on the 4th side. Figopara and Manibux have the same value in Table 5. But to if need to seperate Manibux’s customer base is children who under 18 years old . Manibux gives the parents a “personal child finance” services with moneyboxes.

Table 5: Personal Finance Services Firms in Türkiye and Germany

PERSONAL FINANCE FIRMS	Sales Revenue	PERSONAL FINANCE FIRMS	Sales Revenue
Trumid Financial	33.300.000	Parasut	15.600.000
Tink AB	157.200.000	FigoPara	2.000.000
Yodlee	89.100.000	KolayBi	5.200.000
Gravity Payments	69.100.000	ManiBux	2.000.000
Clinc	59.720.000	Finmaks	5.000.000
		Lumnion	3.500.000

When the financial technology firms develop the system for a more technological insurance systems, insuretech borns. Demand side as a firm want to add their nominals to the insuretechs and their services to improve their effort. (Cortis et al., 2019, p. 71-85). In Germany Clarck with 41,1 million dollars sales revenue on the first place. OttoNova as a Canadian firm has a serious impact on Germany Friendsurance with 20,7 million is on the 3rd place. Coya with a depreciated value when we compare with other firms on the last place of the Table 6.

On the Türkiye side, Sigortam.net has a overwehlming value for the Turkish insuretech market. Also Egaranti (not related with Garanti Bank) is another startup to firm insurectech Rest of the 3 firm has a value under the 1 million dollar. FonRadar with 250 thousand dollar. Wyseye with 211 thousand dollar. Lastly SmartIR with 158 thousand dollar as an insurancetech firm.

Table 6: Insurance-Tech Firms in Türkiye and Germany

INSURETECHS	Sales Revenue	INSURETECHS	Sales Revenue
Clark	41.100.000	Sigortam.net	8.000.000
Coya	3.500.000	egaranti	1.000.000
OttoNova	34.300.000	Wyseye	211.000
Friendsurance	20.700.000	Fonradar	250.000
		SmartIR	158.000

Entropy index has a result between 0 and Log (n;2) (n:number of firms). If our result closes to zero, that means we have a market with monopolistic behaviour because of the high density. However if the result closes to the Log(n;2), in that way we have a competitive market with, low density. In the lending section we include 5 lending financial technology firms in our analysis. In that way our critical value is “2,32”. Lending firms in Türkiye has a comperative market structure. For payment sector we used 5 firm so our critical value has the same amount with the lending sector. Entropy in payment sector shows us the “1,27” result. Which is we can called this sector as a moderate-monopol or oligopol. In personal finance sector we used 6 firm. In that way our critical value raised to 2,58. Entropy index for 6 personal finance firm is 2,17 which means it is a highly competitive market structure. Also there are 5 insuretech firms in our index model. For 5 firm critical value is still 2,32. Our index result 0,91 shows us a highly non-competive market structure in insuretech market.

Table 7: Entropy Index Results for Turkiye

TURKIYE	Entropy index result	Critical Value Log(n;2)
Lending	1,55	2,32
Payment	1,27	2,32
Personal Finance	2,17	2,58
Insuretech	0,91	2,32

4.ANALISE THE FACTOR THAT AFFECT THE FINTECH COMPETITION LEVEL

The entropy index allows us to conduct an inter-company sector density analysis by looking at the product revenues of the companies included in the analysis. Unlike in the N index, entropy includes more firm profile within. Calculating system for entropy has a logarithm base. Results are changing from 0 to Log’s term. We calculate the logarithm term like; Log(2;n). In that formula “n” represents the number of firms. In a chronological timeline to calculate the index, we need to find the firm’s share compared to whole market.

$$E = \sum_{m=1}^{N} X_m \, log_2 \, {}^{1}\!/_{x_m} \tag{1}$$

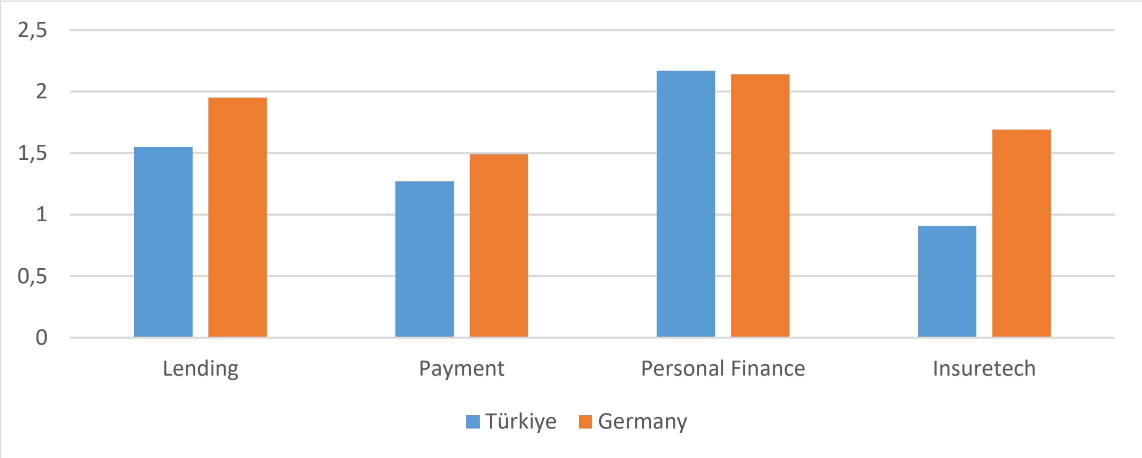
To find the market share we divide the firm’s sales revenue with the total revenue of the whole market. After that we can represent the share of firms as ” X_m”. For the logarithm value we can write this equation like 1 divided by ” X_m”. Lastly the logarithm value for the index will be like this; $log_2\left(\frac{1}{x_m}\right)$. For entropy index we multiply X_m with $log_2\left(\frac{1}{x_m}\right)$. For every firms. Interpretation for the index will be like this; if the result is getting closer to zero then we can interpret the sector as a monopolistic behaviour. If the result is getting closer to Log(2;n), then we can say the sector has a competitive market.

Table 8: Entropy Index Results for Germany

GERMANY	Entropy index result	Critical Value Log(n;2)
Lending	1,95	2,58
Payment	1,49	2
Personal Finance	2,14	2,32
Insuretech	1,69	2

There are 6 lending firms in our index, so critical value for lending is 2,58. We can say lending firms in Germany has a competitive market structure. After that for payment sector with 4 firms our critical value is 2. Result is payment sector has a non-competitive market structure. We have 5 personal finance firm in this analysis. So our critical value for personal finance sector is 2,32. Result shows that personal finance sector has a competitive market structure. We added 4 insuretech firms in our index and results showed us Insuretech in germany has a competitive market structure.

Graph 1: Entropy Results Comparing between Turkiye and Germany



In graph 1 we must consider the critical values to make a better interpretation. The study found the critical values for each sector in Table 7 and Table 8 for your consideration. In that way lending sector in Türkiye has a lower competitive structure than Germany. In the payment sector, the gap between in two countries is getting wider. Personal finance provides a more competitive environment. On the insure tech side we can observe the biggest gap for all the sectors.

4. CONCLUSION

If we had an arrangement to write the firms as a factor, we can get 4 factors for each sector. After that we can take those factors as a key to find the determiners in financial technology competitions. Lending is an fintech service's fundamental to build a decentralized finance structure globally. Lending can be represented as a factor of "service" as a fintech competition factor. Main thing in the description of "service" is comes from the opportunity cost. When the traditional banking's lending system didn't preffered financial technology firms comes with P2P etc. lending systems.

On the other hand payment sector in financial technology firms can represent the "easy processing". Compare with traditional banking, fintechs' biggest revalution is having the easier ability to using process. On the household side it can be includes taxes, fees, bills, tickets etc., also it can be using for international shipment payments, trading fees. Personal finance is another key sector for fintech. If you don't believe in sapiens advisements for your financial portfolio, AI can help that to managing yours.

The personal finance sector can be represented as "management" factor. There can be lots of fractions fort his sector like financial management for elder people to unborn. Table 1 shows the financial technology firms getting place in this study. On the Türkiye's Personal Finance section we can observe the "Manibux". Manibux is a great example fort his study. Manibux gives the children a financial path with their pocket Money. For creating a balanced portfolio, consulting for investments, valuation operations, stock portfolio, Exchange operations etc. we use the personal finance instruments as a individual or firm. But financial technology gives us a different perspective with AI-based financial consulting. AI uses some complicated ratios to make a sustainable forecasts.

After that, it creates a portfolio to valuation our financial capital. Lastly, the insure tech firms one of the fintech's omen. We can give the insure tech firms as a factor name of "security". Insurance technology-based firms intends to make integration for traditional insurance systems into technological-based systems. However, the sector of lending firms in Türkiye's results has a less comperative when we compare with Germany. Germany has 100 basis points more competitive than Türkiye. Lending sector can be bound as trust without other ratios. Türkiye's economical structure and crysis enviroment can be the creation of less-competitive market.

On the other hand Payment sector has the competitive market results for both country. Especially after the Covid-19, digital payment systems has a big role in our life standarts. On the nominal perspective Germany still have the more competitive enviroment on the payments sector more than Türkiye. But in this sector there are no enormous cliffs between two country. Other sector from fintech is Personal Finance. Personal Finance is the most competitive-environment sector when we compare with other sectors. Both Türkiye and Germany has the almost same bu on the critical value side there can be change about 0,2. But for entropy index they both still have the competitive market structure with low density. On the insuretech side observation is more clearly. Comparing with Germany, Türkiye has a enourmously high density in insuretech sector. Biggest firm in the sector eliminate the other firms with its market share. Insurancetech firms in turkey can have sustainable and big portion funds for their company, however one firm's share is ruined the competition enviroment. There are so many factors to explain those cliffs between two country. That topic can be the question for another study. But Türkiye delayed their financial technology investments lately. Currently it's became a hard problem to catch other financial technology firms' share. Although individuals prefer technology-based products in their financial transactions, especially after the pandemic, the perception of fintech should have an important place in the society's perspective for sectors other than the payment sector. On the Türkiye side, insuretechs are the good examples for that prediction sentence. It was obvious that Germany would show a significant victory in the comparison between Turkey and Germany, which has the 4th largest fintech infrastructure in Europe today. However, such a study was essential in order to see some of the values that should stand out in a society like Turkey, where financial technologies have not fully spread to the society and fintech awareness has not been formed. According to growth theories, countries can converge or even surpass their competitors in the financial technology sector through R&D efforts. However, for all these, a serious technology-based payment system must first replace the traditional payment instruments in society. When society accepts such a revolution, the competitive environment of financial companies will increase even more due to increasing demand.

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PREPAYMENT AND DEFAULT RISK: A REVIEW

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ABSTRACT

Purpose- The main purpose of this article is to make a comprehensive review of existing studies on prepayment and default (competing risk). This review enables to shed light on the main determinant of prepayment and default as well as on methods used to model competing risk.
Methodology- A comprehensive review of existing studies/articles.
Findings- More recently proposed machine learning methods (Random Survival Forest and Random Competing Risks Forests, as well as the DeepHit model and Dynamic DeepHit model) enable to take into account the complex/no-linear response of prepayment and default to their determinant more efficiently.
Conclusion- To model properly/correctly the prepayment and default risks it is important to consider the fact that the exercise of the prepayment option brings an end to the default option, and vice versa. These both risks should be modelled together: competing risk. Furthermore, models/methods accounting the complex/no-linear impact of explanatory variables on prepayment and default risks should be used; such as the Random Survival Forest and Random Competing Risks Forests, as well as the DeepHit model and Dynamic DeepHit model.

Keywords: Prepayment risk, default risk, multinomial logit models, multi-state model, random survival forest, Dynamic DeepHit model
JEL Codes: G10, G12, C58

1. INTRODUCTION

A mortgage loan is an agreement between a lender, known as the mortgagee, and a borrower, known as the mortgagor. Within this contract, the mortgagee and mortgagor establish various aspects of the loan, such as its size, repayment schedule, attached life insurance policy, interest rate, collateral, and other relevant details. The mortgagors may unexpectedly default on or prepay the loan. They possess loans that contain American straddles, which are combined call and put options, sold by the mortgagee.1[1] The prepayment or default of loans exposes the mortgagee to several risks, including credit risk, interest rate risk, liquidity risk, mispricing towards customers, and mispricing towards special-purpose vehicles (securitization). To assess and mitigate these risks, as well as for asset-liability management (ALM) purposes and to comply with accounting rules by marking their banking books to market, banks need to evaluate the prepayment and default risks associated with mortgage loans.

Modelling prepayment and default in financial analysis and risk management is of significant importance for financial agents, portfolio managers as well as for policymaker several reasons. Prepayment and default events can have a substantial impact on the risk profile of loan portfolios. By accurately modelling these events, financial institutions can better assess and manage the associated credit and interest rate risks. Furthermore, proper modelling of prepayment and default allows investors and market participants to accurately value cash flows and expected returns of mortgage-backed securities (MBS) and other asset-backed securities (ABS), aiding in investment decisions and pricing. Similarly, lenders and investors need reliable models to price mortgage loans, estimate the expected cash flows, and assess the risk associated with prepayment and default. These

models help in determining appropriate interest rates, loan terms, and risk premiums. In term of regulatory frameworks, such as Basel III, require financial institutions to assess and adequately reserve capital against potential credit losses. Robust prepayment and default models assist in estimating expected credit losses, ensuring compliance with regulatory capital

[1] The borrower receives two options: prepayment as a call option and default as a put option.

requirements. Prepayment and default models provide also valuable insights for strategic decision-making. Lenders can evaluate the impact of different loan products, underwriting standards, and risk management strategies on prepayment and default rates, enabling them to optimize their loan origination and servicing processes. Finally, prepayment and default behavior can reflect broader economic trends and market conditions. By incorporating these models into macroeconomic analysis, policymakers and researchers can gain insights into the health of the housing market, consumer behavior, monetary policy implications, and potential systemic risks.

A mortgage loan can end due to two factors: prepayment and default, which represent competing risks. In the context of mortgage loans, competing risks arise because exercising the prepayment option results in the termination of the default option, and vice versa (Ambrose and Sanders, 2003). Competing risks modelling has gained popularity in analyzing duration data where an event can have multiple causes of termination across various fields, including economics, finance, and risk management.

Prepayment and default risks can be assessed using either financial frameworks or econometric methods rooted in behavioral analysis. Financial methods rely on option pricing models and are commonly employed in pricing callable securities or corporate loans (Chen, 1996; Cheyette, 1996; Deng et al. 2000; Longstaff, 2002; Levin and Davidson, 2005). According to this approach, the rational exercise of the call option by the mortgagor for prepayment or default occurs only when the option is "in the money." In other words, the actual value of the asset should exceed the remaining mortgage balance plus transaction costs. By employing option pricing theory and models, this approach enables the calculation of prepayment risk, default risk, and the value of the mortgage.

However, mortgagors often do not exercise their options rationally. In fact, some mortgagors choose to prepay or default even when it is not financially advantageous, while others fail to exercise the option when it would be beneficial to do so. This irrational behavior among mortgagors can primarily be attributed to behavioral factors. Empirical evidence has shown that prepayment risk is mainly influenced by factors such as refinancing considerations (coupon effects, interest rates, yield curve), personal motives (job changes, relocation, divorce, increased household income, emigration, etc.), and market conditions (business cycle, economic situation, housing market conditions, etc.). As for default risk, its primary determinants are house equity, loan-to-value (LTV) ratio, loan-to-income (LTI) ratio, and debt-coverage ratio (DCR). Additionally, the default rate is influenced by other borrower and loan-specific characteristics, as well as macroeconomic variables.

To address these components, statistical approaches have been proposed and utilized to model and quantify default and/or prepayment risks. Previous studies mostly examined these risks separately, disregarding the fact that they are interdependent. A defaulted loan cannot be prepaid, and a prepaid loan cannot default. Therefore, it is essential to investigate them as competing risks. Several authors have employed competing risk methods to analyse prepayment and default risks in residential mortgages (Ambrose and Capone, 2000; Ambrose and LaCour-Little, 2001; Clapp et al., 2001; Deng et al., 2000). Ciochetti et al (2002) and Ambrose and Sanders (2003) investigated prepayment and default risks (competing risks) in commercial mortgages. Traditional approaches, such as multinomial logistic models, multi-state models, and those based on the Cumulative Incidence Function (CIF), have been commonly used in existing studies to analyse these competing risks. These models rely on functional forms and predominantly consider the linear impact of covariates. However, mis specifying the model can have adverse effects on the results. Additionally, some authors have demonstrated the nonlinear impact of covariates on prepayment and default risks (Sirignano et al., 2018). To overcome these limitations, machine learning and deep learning methods have been introduced. Ishwaran et al. (2014) introduced the Competing Risks Forest method, which is based on the random forest technique and Random Survival Forest (RSF). Lee et al. (2018) developed the DeepHit model, and Sirignano et al. (2018) proposed a deep learning multi-state method to investigate competing prepayment and default risks. These methods directly estimate the CIF, model the nonlinear effects and interactions of covariates, and are free from model assumptions. By not assuming a specific underlying stochastic process, these models allow for a flexible relationship (both linear and nonlinear) between covariates and risks over time.

2. LITERATURE REVIEW

Prepayment rate and default rate have their own determinants as well as some common explanatory variables such macroeconomic and financial variables. These specific and common explanatory variables are presented in what follow.

2.1. The Main Determinants of Prepayment Risk

Determinants of prepayment are often classified into four classes (Hayre, 2003; Jacobs et al., 2005): Refinancing components, Housing turnover, Defaults, and Curtailments.

Refinancing components: The incentive to refinance is closely tied to the movement of interest rates. When market rates significantly drop below the coupon rate, it may trigger the option to prepay for fixed-rate loans. Conversely, for floating-rate loans, an increase in interest rates can lead to prepayment. However, it has been observed that this incentive is not always rational in practice (Hayre, 2003; Jacobs et al., 2005). In the study conducted by Sirignano et al. (2018), they discovered a complex relationship between the actual prepayment rate and the prepayment incentive, which is measured by the difference between the initial mortgage rate and the prevailing market rate. Moreover, they observed that the sensitivity of prepayment rates to changes in the incentive varied significantly in magnitude and direction. According to these authors, the refinancing component exhibits a nonlinear impact on the prepayment rate.

Mortgagors consider not only the current observed interest rates but also the anticipated future movement of interest rates when deciding whether to prepay or not. The expected future interest rate dynamics are often assessed by examining the shape of the yield curve (Goodarzi et al., 1998; Ambrose and Sanders, 2003). In their analysis of prepayment and default risk, Ambrose and Sanders (2003) incorporated the spread between the current contract interest rate and the 10-year Treasury rate as well as a measure of the term structure. The term structure, which serves as an indicator of market expectations, is calculated as the difference between the 10-year Treasury bond rate and the 1-year Treasury bond rate. Moreover, building on the findings of Kau et al. (1993), Ambrose and Sanders (2003) also took into account the volatility of the 10-year Treasury rate. Kau et al. (1993) discovered that interest rate volatility negatively influences the prepayment rate. The results obtained by Ambrose and Sanders (2003) revealed that the yield curve exerts a negative and statistically significant impact on both the prepayment and default rates.

In relation to coupon effects, a lower coupon rate will result in a slower pace of prepayment. The coupon rate is influenced by borrower and loan-specific factors, as well as the year in which the loan was originated. Borrowers with higher credit scores are typically offered lower coupon rates compared to those with lower scores. Additionally, during periods of high interest rates, such as inflationary periods, the proposed coupon rates are higher than during periods of lower interest rates. This situation predominantly arises during economic recessions and times of crisis.

Housing turnover: The rate of prepayment can also be influenced by personal motivations and seasoning effects. Personal reasons may include factors such as job changes or relocations, divorce, increased household income, emigration, and credit score. Several authors, including Agarwal and Taffler (2008), Consalvi and di Freca (2010) and Sirignano et al., (2018), have found that higher credit scores have a positive impact on the prepayment rate.

Seasoning effects are closely associated with the business cycle, the overall economic situation, and prevailing conditions in the housing market. During a booming housing market, the rate of prepayment tends to increase. Hoff (1996) found that the likelihood of prepayment for 30-year Fixed-Rate Mortgages (FRMs) is influenced by upward trends in housing prices and personal income growth. This probability also rises during expansionary periods, as more job changes occur and unemployment decreases.[2] While most existing studies have found limited or no evidence for the influence of unemployment rates on prepayment (Deng, 1997; Elul et al., 2010; Foote et al., 2010). Sirignano et al. (2018) discovered that unemployment rates are the most influential factor in explaining borrower behavior, particularly in terms of prepayment. According to their findings, the relationship between prepayment and unemployment is highly nonlinear and heavily dependent on the borrower's credit score and the prevailing level of unemployment. An increase in the unemployment rate affects the gap between the prepayment rates of borrowers with high and low FICO scores. Similarly, Agarwal and Taffler (2008) put forth the argument that a decrease in borrower credit quality, as measured by the Fair Isaac Company (FICO) score, would diminish the likelihood of prepayment. They also asserted that similar effects can be observed when there is an increase in interest rates and the unemployment rate. In other words, lower borrower credit quality, higher interest rates, and a rise in the unemployment rate all contribute to reducing the probability of prepayment.

Loan-specific characteristics play a crucial role in determining the prepayment rate. Factors such as the type of mortgage product, loan size, and remaining time until maturity have been identified as important determinants (Jacobs et al., 2005; Smith et al. 2007). Additionally, Smith et al. (2007) discovered that the locations of real estate properties, interest rates, and loan amounts borrowed also exert a significant influence on prepayments.

2.2. Determinants of Default Rates

The main determinants of default are the House equity, the Loan-to-value (LTV), the Loan-to-income (LTI), and the Debt-Coverage-Ratio (DCR). Default rate is also impacted by other borrower, loan specific features, and macroeconomic variables.

The significance of decreasing and potentially negative home equity in relation to the default rate has been highlighted in several studies (Vandell, 1978; Campbell and Dietrich, 1983; Bajari et al., 2008). Home equity refers to the difference between the value of the property and the remaining loan balance. According to the option pricing framework, borrowers strategically default when they enter a negative equity position.[3] Empirical evidence from authors such as Mayer et al. (2009) and

[2] In contrast, in downturn situation prepayments are triggers by defaults.

[3] See Vandell (1995) for a review of empirical literature.

Goodman et al. (2010) have supported the primary role of negative equity in explaining mortgage defaults. However, these findings have been challenged by other authors who argue that homeowners do not default immediately upon reaching negative equity but rather experience a delay (Bhutta et al., 2010; Deng et al., 2000; An and Qi, 2012; Guiso et al., 2013; Campbell and Cocco, 2015; Sirignano et al., 2018). Bhutta et al. (2010) and Guiso et al. (2013) have demonstrated through different methods that equity shortfalls must exceed 50% before strategic default becomes prevalent. In the case of Sirignano et al. (2018), they discovered a nonlinear relationship between home equity and the default rate. Specifically, their findings indicated that the sensitivity of the delinquency rate to changes in house prices strongly depends on the realized appreciation and the state of unemployment. Moreover, according to some authors, defaults can be explained by a combination of negative equity and affordability shocks, known as the "double-trigger hypothesis" (Bajari et al., 2008; Bhutta et al., 2010; Elul et al., 2010; Gerardi et al., 2013; Lydon and McCarthy, 2013; Gyourko and Tracy, 2014; McCarthy, 2014; Sirignano et al., 2018). Bhutta et al. (2010) found that defaults are influenced by a combination of negative equity and income or employment shocks.

The standard contingent claims approach to mortgage pricing suggests that default is primarily explained by the loan-to-value (LTV) ratio. Several authors have demonstrated the positive impact of the LTV ratio on the likelihood of negative home equity and mortgage default (Schwartz and Torous, 2003; Mayer et al., 2009; Campbell and Cocco, 2015). For example, Campbell and Cocco (2015) observed that the unconditional default probabilities significantly increase for LTV ratios exceeding ninety percent. However, in contrast to these findings, a few authors have not found a significant relationship between default/prepayment and the LTV ratio (Ambrose and Sanders, 2003).

The default rate of loans associated with income-generating properties, such as hotels, commercial properties, or traditional multifamily loans, is also influenced by the debt-servicing coverage ratio (DCR) (Ambrose and Sanders, 2003). The DCR is a measure that assesses the property's income relative to its debt obligations. Properties with higher DCR are considered more profitable, while those with low DCR indicate potential financial challenges. Generally, properties with an exceptionally low DCR face difficulties in repaying loans on time. Lenders prefer to provide loans to borrowers with higher DCR as it signifies a greater ability to meet debt obligations. The impact of DCR on the default rate depends on the level of property risk. Riskier property types, such as hotels or motels, may require a higher DCR to secure a loan compared to traditional multifamily or commercial properties (e.g., apartment buildings or shopping centers with anchor tenants).

Ambrose and Sanders (2003) found no significant influence of Loan-to-Value (LTV) and Debt Coverage Ratio (DCR) on the rates of prepayment and default. Their findings align with the explanation provided by Archer et al. (2001). According to Archer et al., LTV and DCR are factors that are determined by the loan origination process itself. Additionally, lenders take into consideration the risk of default when offering mortgage terms. For example, applicants with higher risk loans may be required to provide a larger down payment, resulting in a lower LTV ratio. Conversely, lower-risk applicants may be allowed a smaller down payment, leading to a higher LTV ratio. Similarly, higher-quality borrowers may have a lower Debt Coverage Ratio (DCR) requirement, while lower-quality borrowers may face a higher DCR requirement.

The loan-to-income (LTI) and mortgage-payments-to-income (MTI) ratios are also crucial factors in determining default probabilities. Campbell and Cocco (2015) explain that while the loan-to-value (LTV) ratio measures the initial equity stake of the household, the LTI and MTI ratios reflect the initial affordability of the mortgage. According to Campbell and Cocco (2015), the LTI ratio impacts default rates through a distinct mechanism. They argue that a higher initial LTI ratio does not directly increase the likelihood of negative equity; instead, it reduces mortgage affordability, making it more likely for borrowing constraints to become binding. This, in turn, lowers the threshold of negative home equity that triggers default, leading to an increase in default probabilities. Our model suggests that mortgage providers and regulators should consider the combined effects of LTV and LTI ratios and avoid controlling these parameters in isolation.

Apart these aforementioned factors, certain loan-specific characteristics also play a significant role in determining default rates. These include the age of the mortgage, borrowed amounts, origination year, and time until maturity. Some authors, such as Lawrence et al. (1992) and Schwartz and Torous (2003), have identified the impact of mortgage age on default rates. Smith et al. (2007) discovered that interest rates, loan amounts, and the proportion of mortgages also have a positive influence on defaults. Lawrence et al. (1992) conducted an analysis of mortgage loan defaults, taking into account borrower characteristics, mortgage durations, terms and conditions, economic factors, and default costs. While many of these variables have a significant impact on default behavior, mortgage leverage and repayment pressure emerge as the most influential factors.

Borrower-specific variables also play a crucial role in determining default events. In fact, defaults can be triggered by various stressful events experienced by borrowers, such as job layoffs, divorces, and so on (An and Qi, 2012).

Several economic and financial variables also serve as important determinants of default rates (Smith et al., 2007; LaCour-Little, 2008; Campbell and Cocco, 2015). An increase in interest rates has a positive impact on default rates for adjustable-rate mortgages (ARMs) due to the resulting higher required payments, while the opposite is true for fixed-rate mortgages

(FRMs) (Campbell and Cocco, 2015). Additionally, Sirignano et al. (2018) discovered that macroeconomic variables, particularly the unemployment rate, interact in complex ways with various other factors such as loan-to-value ratios, mortgage rates, and house price appreciation. They also found that the impact on prepayment and default rates is nonlinear.

2.3. Additional Information on Prepayment and Default Determinants

As presented in the previous section, main determinants of prepayment and default are:

The risk of prepayment is influenced by various refinancing factors, including financial incentives, the term structure of interest rates, the yield curve, and spreads. Additionally, prepayment is affected by variables associated with housing turnover. These variables encompass economic indicators such as GDP and the unemployment rate, housing market conditions indicated by the house price index (HPI), loan-specific characteristics such as loan age, loan type, loan amount, origination date, and property location, as well as borrower attributes like age, income, and credit score (FICO).

The default rate is primarily influenced by various factors, including house equity, loan-to-value (LTV) ratio, loan-to-income (LTI) ratio, debt-servicing coverage ratio (DCR), macroeconomic variables such as the unemployment rate, GDP, and policy rate, loan-specific variables such as loan age, loan type, time to maturity, origination date, and property location, as well as borrower characteristics like age, income, and credit score (FICO).

2.3.1 Lagged Values and Time-Varying Values

According to several authors (Goodarzi et al., 1998; Elie et al., 2002; Li et al., 2019), it has been observed that mortgagors tend to react to market conditions with a delay of several weeks. In light of this, these authors incorporated lagged values of explanatory variables in their analyses. For example, Goodarzi et al. (1998) considered lagged values ranging from 0 to 12 weeks for variables such as Burnout, Yield Curve Slope, and Present Value Ratio. Li et al. (2019) examined default and prepayment rates as competing risks using a multinomial logit model, and they included lagged values of explanatory variables (loan-specific, personal, and macroeconomic variables) from three periods (months) prior. Elie et al. (2002) stated that borrowers' reactions to changes in market rates occur between 4 to 7 months later. In comparison to these mentioned studies, most existing research on prepayment and default risks did not take into account the lagged values of explanatory variables.

In addition, the majority of existing studies on prepayment and default risks have focused on time-invariant covariates, using only the initial values of the variables. However, certain covariates, such as macroeconomic indicators, loan-to-value ratio (LTV), financing incentives, and credit score, are subject to changes over time. It is more appropriate to consider the current values of these variables, taking into account their time-varying nature. Only a few authors have incorporated time-varying variables into their analyses, such as (Visible Equity, Ambrose and Sanders (2003), Ding et al. (2012), and Sirignano et al. (2018).

2.3.2. Refinancing Incentive Modelling

Determining the refinance incentive is crucial in understanding both the prepayment and default rates. Various methods have been employed to calculate this incentive. The simplest approach involves calculating the refinance incentive as the difference between the loan rate and the market rate, as suggested by Ambrose and Sanders (2003) and Sirignano et al. (2018). Elie et al. (2002) observed that borrowers typically react to changes in market rates with a delay of 4 to 7 months. Taking this delayed reaction into account, they defined the refinance incentive as an average of the spread between the loan coupon rate and the market rate over this time period.

Other methods have also been considered. For example, some authors defined the refinance incentive as the Present Value Ratio (PVR) of the existing mortgage's payments compared to the annuity value of a new mortgage, as proposed by Richard and Roll (1989) and Goodarzi et al. (1998). Jacobs et al. (2005) computed the refinance incentive (RFI) as the net present value of the interest payments saved (until the next interest reset date) if the mortgage could be refinanced at the prevailing interest rate, relative to the size of the loan.

These methods are presented in the Appendix.

2.3.3. Initial and Current LTV and House Equity

Most of existing empirical studies have considered the initial loan-to-value (LTV) ratio, which is calculated as the initial loan value divided by the initial property value. However, it is worth noting that the realized LTV at the event time or a few periods before (referred to as the current LTV) may be a more significant explanatory variable for prepayment and default rates than the initial LTV. The current LTV can be determined by multiplying the initial property value (computed as the initial loan value divided by the initial LTV) and the monthly cumulative return of the house price index, as suggested by Ambrose and Sanders (2003) and Visible Equity. By dividing the current outstanding loan amount by the determined current property value, the current LTV can be calculated. Additionally, the computed current property value (obtained by multiplying the initial property value by the monthly cumulative return of the house price index) allows for the determination of the current house equity. The current house equity is defined as the difference between the property value and the outstanding loan balance.

3. METHODOLOGY

Prepayment risk and default risk have often been modelled separately using survival analysis techniques (Dunn and McConnell; 1981; Brennan and Schwartz, 1985; Green and Shoven, 1986; Deng et al., 2000; Jacobs et al., 2005; Consalvi and di Freca, 2010; Stanton and Wallace, 2011; Nijescu, 2012).

The analysis of prepayment and default as competing risks in existing studies has predominantly relied on hazard models or multinomial logistic models. Multinomial Logit (MNL) models have been commonly employed in the mortgage termination literature to model competing risk events (Clapp et al, 2000, 2001, 2006; Dunsky and Ho, 2007; VisibleEquity; Li et al. 2019). These models are based on a specific functional form and primarily consider the linear impact of covariates. However, the limitations of these models can be overcome by utilizing methods based on machine learning and deep learning.

Ishwaran et al. (2014) introduced the Competing Risks Forest method, which is based on the random forest approach and incorporates elements of the Random Survival Forest (RSF). Lee et al. (2018) developed the DeepHit model, which leverages deep learning techniques. Similarly, Sirignano et al. (2018) proposed a deep learning multi-state method to investigate the competing risks of prepayment and default. These methods directly estimate the Cumulative Incidence Function (CIF), enabling the modelling of non-linear effects and interactions among covariates, and they are free from assumptions imposed by traditional models. By not assuming any specific underlying stochastic process, these models allow for a flexible relationship, both linear and non-linear, between covariates and risks over time. The following sections provide a detailed presentation of these methods.

3.1. Classical Approaches

3.1.1 Survival Analysis

Prepayment risk and default risk have often been modelled separately using survival analysis techniques (Dunn and McConnell; 1981; Brennan and Schwartz, 1985; Green and Shoven, 1986; Deng et al., 2000; Jacobs et al., 2005; Consalvi and di Freca, 2010; Stanton and Wallace, 2011; Nijescu, 2012). Survival models are commonly employed to analyse the time elapsed before a specific random event takes place. In our context, the event occurrence time (T) represents either the prepayment time, the default time, or censoring. The survival function, in this case, denotes the probability that the event will not occur until time t: $S(t) = P(T > t)$. The complement of the survival function is the cumulative distribution function, which describes the cumulative incidence of the event of interest up to time t: $F(t) = 1 - S(t) = P(T \leq t)$. The survival function is related to the hazard function h(t), which represents the instantaneous failure at time t, conditional on no occurrence of the event until time t. This hazard function, the cumulative hazard function (H_t) and the survival function (S(t)) are expressed as:

$$
\begin{aligned}
h(t) &= lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t} = \frac{S'(t)}{S(t)} = \frac{f(t)}{S(t)}, && (1) \\
H(t) &= \int_0^t h(u) du = -lnS(t), && (2) \\
S(t) &= exp(-H(t)), && (3)
\end{aligned}
$$

where f(t) represents the density function of the occurrence of the analyzed event.

Understanding the relationship between covariates and survival times (times-to-event) is crucial. However, in many existing studies, this relationship has been investigated by assuming a specific form for the underlying stochastic process, such as the Cox proportional hazards model (Cox, 1972) or the Accelerated Failure Time (AFT) model. These approaches rely on strong assumptions about the underlying stochastic process and the relationship between covariates and the parameters of that process. Additionally, these methods do not account for competing risks, which is an important consideration in many survival analysis scenarios.

When dealing with competing risks, it is important to consider the joint distribution of the event occurrence time and the competing events. Some researchers have utilized classical survival models to study the default and prepayment behavior of loans as competing risks. Proportional hazard models have been commonly employed in these studies (Deng et al., 2000; Ambrose and LaCour-Little, 2001; Pavlov, 2001; Ciochetti et al., 2002; Ambrose and Sanders, 2003; An and Qi, 2012). In the classical model, right-censoring is treated as uninformed or providing no information about the eventual terminal event of the subject.

However, it is important to note that the occurrence of other events leading to termination, besides the main event being analysed, is not uninformed. For example, when modeling default with the Cox Proportional Hazards model, it assumes that default is the terminal event and prepayments are treated as right censored. However, after the point of prepayment, prepaid loans will never default, and thus censoring at that point is not uninformed.

3.1.2. Cumulative Incidence Function (CIF)

To account for competing risks, two formulations of the Cumulative Incidence Function (CIF), representing the probability of failing from cause k before time t, were proposed: 1) CIF based on cause-specific hazard function and 2) CIF based on the sub-distribution.

Cause-specific CIF

The probability that an event occurs in a specific time period [0, t] depends on the cause-specific hazards of the other events (Gray, 1988). The probability of experiencing an event k by time t, determined using the cumulative incidence function (CIF: $F_k(t|x)$), is related to cause-specific hazard function (λ_k) as follows:

$$\begin{aligned} F_k(t|x) &= P[T \leq t, D = k|x], &(4)\\ &= \int_0^t S(s-|x)h_k(s|x)ds = \int_0^t exp[-\int_0^s \sum^K h_l(u|x)du]h_k(s|x)ds, &(5)\end{aligned}$$

where $S(t|x) = P[T \geq t|x]$ is the event-free survival probability function given covariates x. Event k can only occur for those surviving other risks. Regarding the cause-specific hazard function ($h_k(t|x) = f_k(t|x)/S(t|x)$), it describes the instantaneous risk of event k for subjects that currently are event-free. This hazard function is expressed as:

$$h_j(t|x) = lim_{\Delta t \to 0} \frac{P(t \leq T < t + \Delta t, k = j|T \geq t)}{\Delta t} = \frac{f_j(t)}{S(t)}. \qquad (6)$$

The covariates (x), haven an impact on the CIF of event k, are those that change the cause-specific hazard function of event k as well as the cause-specific hazard functions of the competing risks (Ishwaran et al., 2014). Several authors determined the CIF by modelling the cause-specific hazards with the Cox' regression model (Lunn and McNeil, 1995; Cheng et al., 1998; Shen and Cheng, 1999; Scheike and Zhang, 2002, 2003). Other survival method can also be used to model the cause-specific hazard function.

CIF based on the sub-distribution - Fine and Gray (1999)

Fine and Gray (1999) proposed to model the Cumulative Incidence Function (CIF) as:

$$\begin{aligned} F_k(t) &= P(T \leq t, D = k), &(7)\\ F_k(t|X) &= 1 - exp(-\Lambda_k(t)exp(x^T\beta), &(8)\end{aligned}$$

where $\Lambda_k(t)$ is an unknown increasing function and β is a vector of coefficients to be estimated. Fine and Gray proposed to use an inverse of censoring weighting technique to estimate $\Lambda_k(t)$ and β.

Fine and Gray proposed a proportional hazards model for the subdistribution hazard function, specifically for the k_{th} type of event.

$$h_k^{st}(t) = lim_{\Delta t \to 0} \frac{Prob(t \leq T \leq t + \Delta t, D = k|T \geq t \cup (T \leq t \cap D \neq k))}{\Delta t}, \qquad (9)$$

where D represents the type of event that occurred. Each of the K different types of events has its own subdistribution hazard function, which is defined as the instantaneous rate of occurrence of the given type of event in subjects who have not yet experienced an event of that type. The risk set consists of those subjects who are either currently event-free or who have previously experienced a competing event.

This model is also based on strong assumptions related to the hazard rates and on the impact of covariates on model's parameters.

Scheike and Zhang (2011) introduced a class of flexible models for CIF. According to these authors, previously proposed model for CIF are special sub-models of their models (Fine and Gray, 1999; Shen and Cheng, 1999; Scheike and Zhang, 2002, 2003) . The general formulation of their models is given as:

$$h(F_k(t|X,z)) = X^T\alpha(t) + g(z,\lambda,t), \tag{10}$$

where h and g are link functions and α(t) and λ are unknown regression coefficients.

Covariates z are assumed to have proportional effect on CIF whereas covariates X are allowed to change their effects on the cumulative incidence function over time. Any link function can be used. In their study, Scheike and Zhang (2011) retained two classes of flexible models: proportional models (P) and additive models (A); which are expressed as: [4]

$$\begin{aligned} cloglog[1-F_k(t|X,z)] &= X^T\alpha(t) + z^T\lambda, \qquad (P) \qquad (11)\\ -log[1-F_k(t|X,z)] &= X^T\alpha(t) + (z^T\lambda)t, \qquad (A). \qquad (12) \end{aligned}$$

3.1.3. Multi-State Models

Lando and Skodeberg (2002) proposed a Markov multi-state model of transitions between multiple states in continuous time.[5] This model captures movements between n states where the probability of moving away from the current state depends on the previous state. Survival analysis is a special case with two states, "alive" and "dead". Competing risks can also be considered as a special case, where there are multiple causes of termination (death). The transition intensities from the initial state X(t) at time t to the next state are defined as:

$$q_{rs}(t, X(t), \Im_t) = lim_{\delta t\to 0} P(X(t+\delta t) = s|X(t) = r, X(t), \Im_t)/\delta t, \tag{13}$$

where r, s = 1, ...,K represent the states. The transition intensities can depend on covariates (X(t)), the time (t), and the "history" of the process up to that time ($\Im_t$).[6] [7] The KxK matrix Q is composed with the transition intensities q_{rs}. The rows of this matrix sum to zero, so that the diagonal entries are defined by $q_{rr} = -\sum_{r\neq s} q_{rs}$.

An individual may change states several times (t_1,...,t_n are event times).

In semi-Markov (clock-reset) models, the transition intensity ($q_{rs}(t)$) from state r to s at time t depends only on the time t since entry into the current state, and the time since the beginning of the process is not taken into account. Whereas, in an inhomogeneous Markov (clock-forward) model, the time t represents the time since the beginning of the process, but the intensity $q_{rs}(t)$ does not depend further on $\Im_t$.

Multi-state models can be represented with of survival models. In the multi-state model, each transition intensity can have a corresponding survival model (time-to-event model), with hazard rates representing the transition intensities q_{rs}. Precisely, an individual who entered in state r at time t can transit to n_r competing risks (s_1,...,s_{nr}) at time t + δ_t. They are then n_r survival models related to the state r and $\sum_r n_r$ models over all states r. If the individual transits to state s_k at time (t+δ_t) then the transitions to all other states are censored at this time (t + δ_t).

Retained survival models can be parametric models as well as semi-parametric. Parametric models can include different probability distributions such as Weibull, Gompertz, gamma, log-logistic, lognormal, and generalized gamma. Parametric models are useful for extrapolating beyond the time horizon in the existing data (Jackson, 2018).

4 Other link functions are also possible.

5 Lando and Skodeberg (2002) pointed out significant advantages of this continuous multi-state model over the discrete time, "cohort method" approach.

6 This history represents the states previously visited and the time spent in them.

7 For time-homogeneous models, the transition intensities are determined as:

$$\begin{aligned} q_{rs}(t, X(t)) &= q_{rs},\\ q_{rs}(z(t)) &= q^0_{rs} exp(\sum_{k=1}^{K} \beta_{rs,k} x_k),\\ ln(q_{rs}(X(t))) &= ln(q^0_{rs}) + \sum_{k=1}^{K} \beta_{rs,k} x_k, \end{aligned}$$

where X_k, k = 1, 2, . . . , k is a set of exogenous variables affecting the instantaneous risk of going from state r to state s.

3.1.4. Multinomial Logit (MNL) Models

Multinomial Logit (MNL) models were used to model competing risk events in mortgage termination literature (Clapp et al, 2000, 2001, 2006; Dunsky and Ho, 2007; VisibleE-quity; Li et al. 2019). Multinomial logistic regression assumes mutual independence of choices for a given record during an observation period. For example, each periodic (monthly for example) observation is treated as though it were independent from the prior observation. Furthermore, multinomial logistic regression directly estimates the probabilities of each outcome which sum up to one. In this study, at each period t, the possible outcomes are active ($D_i = 0$), defaulted ($D_i = 1$) and prepaid ($D_i = 2$) for each loan. The probability of each outcome category conditioning on the covariates are given as:

$$P(D_i = 0|x_i) = \frac{1}{1 + \sum_{k=1}^{2} exp(\beta_k^T x_i)}, \quad (14)$$

$$P(D_i = k|x_i) = \frac{exp(\beta_k^T x_i)}{1 + \sum_{k=1}^{2} exp(\beta_k^T x_i)} \qquad k = 1, 2, \quad (15)$$

where x_i is a vector of observed independent variables including borrower characteristics w_i, loan features λ_i and macroeconomic factors z_i ($x_i = (w_i; \lambda_i; z_i)$). β represents the vector of parameters to estimate.

The MNL method consists of fitting the ratio of the expected proportion for each response category over the expected proportion of the reference category. The logit functions are defined as

$$ln(\frac{P(D_i = k|x_i)}{P(D_i = 0|x_i)}) = \beta_k^T x_i, \qquad k = 1, 2, \quad (16)$$

The parameters are estimated by using maximum likelihood function defined as

$$lnL = \sum_i ln(P(D_i)|x_i)). \quad (17)$$

The probabilities, defined in eq. 14 and 15, represent the probabilities of staying active, prepaying, or defaulting during a particular period given that the loan was active at the beginning of that period. The probability of these events after few periods can be deduced.[8] For example, the probability that the event k realizes for a certain loan in the future at time T knowing that it was active at time t (t < T) is simply the product of probabilities obtained from eq. 14 and 15, as

$$P_k(T, t) = P(D_i = k|x_i)(T)P(D_i = 0|x_i)(T - 1)...P(D_i = 0|x_i)(t + 1). \quad (18)$$

Clapp, Deng, and An (2006) presented evidence that the multinomial logistic regression model is an attractive alternative to proportional hazard models in a case of mortgage termination, by either refinancing, moving or defaulting. However, compared to proportional hazard models' multinomial logistic regression enables to predict the occurrence of the events over the retained period rather than when they will take place.

3.2. Methods based on Machine Learning and Deep Learning

Several researchers have highlighted the non-linear effects of explanatory variables on prepayment and default rates (Elie et al., 2002; Dunsky et Ho, 2007; Elul et al., 2010; Agarwal et al., 2012; Sirignano et al., 2018). In particular, Sirignano et al. (2018)

discovered that many explanatory variables have a highly non-linear impact on borrower behavior, specifically on prepayment and default events. These authors emphasized that interactions between variables play a significant role in generating the non-linear effects. They also noted that the influence of a covariate on the dependent variable (prepayment, default, etc.) can be influenced by one or more other covariates.

Furthermore, the non-linear relationship may arise due to changes in the sensitivity of borrower behavior with respect to an explanatory variable, depending on the level of that variable (Sirignano et al., 2018). For example, Sirignano et al. (2018) observed that the sensitivity of borrowers to fluctuations in unemployment rates is not constant (linear), but varies significantly with the level of unemployment itself as well as the level of other variables.

There are methods available that allow for capturing the non-linear impact of covariates on dependent variables. In the Cox model, the nonparametric baseline hazard function can capture the non-linear influence of covariates on prepayment and

[8] Multinomial logistic regression assumes mutual independence of choices for a given record during an observation period. For example, each periodic (monthly for example) observation is treated as though it were independent from the prior observation.

default (Sirignano et al., 2018). Additionally, both the Cox and logistic regression models can incorporate non-linearity by including quadratic or other nonlinear transformations of specific variables (Agarwal et al., 2012; Sirignano et al., 2018). For example, Agarwal et al. (2012) introduced the squared loan age as a risk factor in addition to the loan age itself.

Another approach, used by Elul et al. (2010), involves discretizing continuous variables such as the loan-to-value ratio. However, this method requires identifying and analyzing the variables that need to be transformed, which can be time-consuming, especially in studies with a large number of explanatory variables.

The non-linear impact of covariates and the consideration of competing risks can also be addressed using methods based on machine learning and deep learning. There have been approaches proposed that combine survival analysis with machine learning techniques. For example, Ishwaran et al. (2008) introduced random survival forests for competing risks, while Sirignano et al. (2018) utilized a deep learning model to capture all non-linear effects, including variable interactions of any order, in the data. The deep learning model was employed to model different states of mortgages, including prepayment and default. Similarly, Lee et al. (2018) developed the DeepHit model specifically for investigating competing risks. These methods leverage the power of machine learning and deep learning to effectively handle non-linearity and competing risks in survival analysis.

3.2.1. Random Survival Forest - Random Competing Risks Forest

The Random Survival Forest (RSF), initially proposed by Ishwaran et al. (2008), is an ensemble method comprised of randomly grown survival trees. Each tree in the forest is built using an independent bootstrapped sample from the learning data, and random feature selection is applied at each node during tree growth. Similarly, a competing risk forest can be constructed using the same methodology as RSF, with the key difference lying in the splitting rules.

There are two main approaches to building a competing risk forest. The first approach involves growing separate competing risk trees for each event in each bootstrap sample, utilizing event-specific splitting rules to guide the tree growth. The second approach entails growing a single tree in each bootstrap sample, where the splitting rules can either be event-specific or a combination of event-specific rules across the events. The latter approach is more commonly used as it is more efficient and generally sufficient for most tasks (Ishwaran et al., 2014; Hamidi et al., 2017). Precisely, a competing risks forest is grown as follows:

. B bootstrap samples from the original data are drawn. Each competing risk tree is grown by using 63% of the data and the remaining 37% of data (out-of-bag OOB) are used to determine the out-of-bag cross-validated survival as well as variable importance (VIMP) and minimum depth measures for each independent variable.

. Using each bootstrap sample, a competing risk tree is grown based on randomly selected M ≤ p covariates at each node of the tree. The retained variable for splitting each node is the one that maximizes a splitting rule. This rule can be based on generalized log-rank test, Gray's test, or composite splitting rule. The generalized log-rank test is most suitable for selecting variables that affect cause specific hazards whereas Gray's test is most suitable for identifying variables directly affecting cumulative incidence function. These splitting rules and tests are presented in detail in Ishwaran et al. (2014).

. Grow each tree to full size and calculate the cumulative cause-specific hazards for all events (k) for each tree (b).

. Take the average of each estimator over the B trees to obtain its ensemble.

The CIF of the b_{th} tree is defined as:

$$\hat{F}_{k,b}(t|x) = \int_0^t \hat{S}_b(u-|x) Y_b(u|x)^{-1} N_{k,b}(du|x), \quad (19)$$

$$with,$$

$$\hat{S}_b(t|x) = \prod_{u \le t} \left(1 - \frac{\sum_k N_{k,b}(du|x)}{Y_b(u|x)}\right), \quad (20)$$

where $\hat{S}_b(t|x)$ is the Kaplan-Meier estimate of event-free survival. t_j represents ordered event times. $d_k(t_j)$ and $N_k(t)$ correspond to the number of type k events at t_j and in the interval [0, t], respectively. $d(t_j)$ and $N(t)$ represent the number of all events at t_j and in the interval [0, t], respectively. Y(t) is the number of individuals at risk (event-free and uncensored) just prior to t.

The ensemble estimates of the CIF and the cause-k mortality are given as:

$$\bar{F}_k(t|x) = \frac{1}{B}\sum_{b=1}^{B} \bar{F}_{k,b}(t|x), \qquad \bar{M}_k(\tau|x) = \int_0^\tau \bar{F}_k(t|x)dt := \frac{1}{B}\sum_{b=1}^{B} \bar{M}_{k,b}(\tau|x).$$

To determine and compare the performance of models, the ensemble estimates of the CIF and the cause-k mortality are also determined by using out-of-bag (OOB) data as:

$$\bar{F}_k^{OOB}(t|x_i) = \frac{1}{|O_i|}\sum_{b\in O_i}\bar{F}_{k,b}(t|x_i), \qquad \bar{M}_k^{OOB}(\tau|x_i) = \int_0^\tau \bar{F}_k^{OOB}(t|x_i)dt := \frac{1}{|O_i|}\sum_{b\in O_i}\bar{M}_{k,b}(\tau|x_i),$$

where $O_i \subset 1, ...,B$ is the index set of trees. The OOB predicted value for a case is a cross-validation based estimator. It can be used for estimation of the prediction error.

The prediction performance can be measured with the concordance index (C–index); which is related to the area under the receiver operating characteristic curve (Ishwaran et al., 2014). The classical concordance index represents the probability that, in a randomly selected pair of cases, the case failing first had a worse predicted outcome. In the case of competing risk forest, the ensemble prediction of the CIF is concordant with the outcome if either the case with the higher cause-k mortality has event k before the other case haven an event of cause k or a competing event. Case (individual) i has a higher risk of event k then case i' if $\bar{M}_k(\tau|x_i) > \bar{M}_k(\tau|x_{i'})$. The time-truncated concordance index for competing risks, proposed by Wolbers et al. (2013), is given as:

$$C_k(\tau) = P[\bar{M}_k(\tau|x_i) > \bar{M}_k(\tau|x_{i'})|T_i^0 \le \tau, \delta_i^0 = j \quad and \quad (T_i^0 < T_{i'}^0, \quad or, \delta_{i'}^0 \ne k)]. \quad (21)$$

Regarding the prediction error, it can be measured with the integrated Brier score (BS), which is the squared difference between actual and predicted outcome (Ishwaran et al., 2014). A static and time dependent BS were proposed (Graf et al., 1999; Gerds and Schumacher, 2006). To assess the performance of the ensemble CIF, the integral of the time-dependent BS is given as:

$$IBS_k(\tau) = \int_0^\tau BS_k(t)dt = \int_0^\tau E[I(T_i^0 \le t, D_i = k) - \bar{F}_k(t|X)]^2 dt. \qquad (22)$$

The importance of covariates is determined with the variable importance (VIMP) and minimum depth measures. The VIMP measures the increase (or decrease) in prediction error for the forest ensemble when a covariate is randomly "noised-up" (Breiman, 2001). The larger VIMP of a covariate is the higher predictiveness of the variables is. The value of VIMP that is greater than 0.002 is assumed as an effective variable whereas the smaller values of the minimal depth reveal higher predictiveness of the variables.

Minimal depth assesses the predictiveness of a variable by the depth of the first split of a variable relative to the root node of a tree (Ishwaran et al. 2010).

All these measures (concordance index, prediction error, the variable importance (VIMP) and minimum depth and the minimal depth) are determined in-sample as well as out-sample (Out-of-Bag - OOB).

3.2.2. Deep Learning

DeepHit model

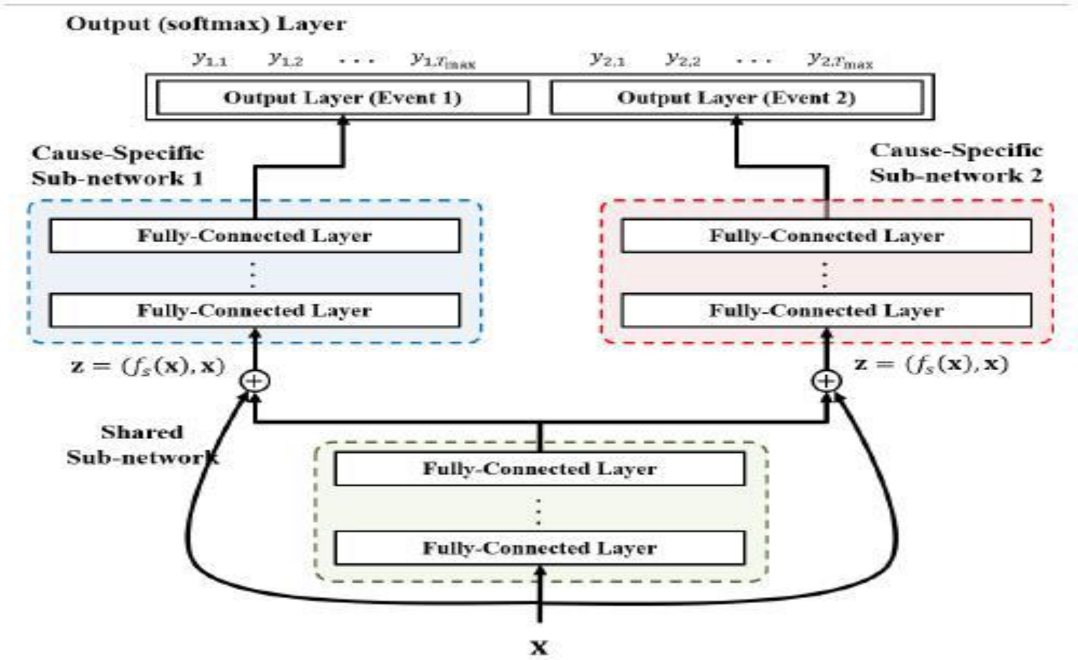
Faraggi and Simon (1995) were the pioneers in applying neural networks to the Cox Proportional Hazard model, which is commonly used in survival analysis. Subsequent authors, such as Katzman et al. (2016) and Luck et al. (2017), expanded on this work by introducing more advanced network architectures and loss functions. These authors relaxed the specific functional relationship between covariates and the hazard function while maintaining other key assumptions. However, their models still assumed a constant hazard rate over time, did not capture the time-dependent influence of covariates on survival, and did not account for competing risks.

In comparison, Lee et al. (2018) developed the DeepHit model, which utilizes a deep neural network to directly learn the distribution of survival times without making assumptions about the underlying stochastic process. Unlike the previous models, the DeepHit model acknowledges that the relationship between covariates and risks may change over time. Additionally, the DeepHit model is capable of handling competing risks, providing a more comprehensive framework for survival analysis.

The network architecture of this DeepHit model consists of a single shared subnetwork and a family of cause-specific sub-networks. In our case, there are two cause-specific sub-networks corresponding to prepayment and to default. The shared sub-network and the k–th cause-specific sub-network (k = 1, ...,K, K = 2 in our case) are formed with L_S ans $L_{c,k}$ fully-connected layers, respectively. The graph 1 represents a DeepHit model with 2 competing risks (K = 2).

By using the covariates x as inputs, the shared sub-network produces a vector of output fs(x) that is common to retained competing events. This vector and the original covariates (X) are used by each cause-specific sub-network as inputs (z = (f_s(x), x)). Each cause-specific sub-network produces a vector f_{ck} (z) as output, representing the probability of the first hitting time of a specific cause k. Precisely, the cause-specific sub-networks are learning the distribution for the first hitting time for each cause in parallel. All outputs represent the joint probability distribution on the first hitting time and event. A single softmax layer is used as the output layer of DeepHit in order to ensure that the network learns the joint distribution of K competing events not the marginal distributions of each event. This output layer produces a probability distribution y = [$y_{1,1}$, ..., $y_{1,T}$, $y_{2,1}$, ..., $y_{2,T}$] representing the probability (P(s, k|x)) that a borrower characterized with features (x) will experience the event k at time s.

Figure 1: Architecture of DeepHit in case of 2 Competing Risk (Lee et al. (2018))



The network is trained by using a loss function based on both survival times and relative risks. The loss function is defined as the sum of two terms: $L_{Total} = L_1 + L_2$, where L_1 is the log-likelihood of the joint distribution of the first hitting time and corresponding event, modified to take account of the right-censoring. As for L_2, based on estimated CIFs calculated at different times, it enables to fine-tune the network to each cause-specific estimated CIF. As Fine and Gray (1999), Lee et al. (2018) defined the CIF function as the probability that a particular event k^* occurs on or before time t^* conditional on covariates x^*. As the true CIF is not known, Lee et al. (2018) used the estimated CIF. For the event k^* the estimate CIF is defined as: $\hat{F}_k^*(t^*|x^*) = \sum_{m=0}^{s^*} y_{k,m}^*$.

Lee et al. (2018) compared the performance of DeepHit model with the performance of other retained model by using the time-dependent concordance index. Compared to the classical concordance index, the time-dependent concordance index enables to take into account the possible change in risk into account.

Dynamic DeepHit Model

The initial DeepHit model allows for predicting competing risks by utilizing the most recent available measurements of retained covariates. In contrast, the Dynamic-DeepHit model goes a step further by incorporating longitudinal data that consists of infrequently repeated measurements. This updated model can dynamically update survival predictions for one or multiple competing risks. Importantly, the Dynamic-DeepHit model learns the distributions of time-to-event without assuming any specific underlying stochastic models for the longitudinal and time-to-event processes.

The Dynamic-DeepHit model is constructed as a multi-task network, comprising of a shared subnetwork and a family of cause-specific subnetworks. The shared subnetwork consists of two components: i) an RNN structure that handles the longitudinal data, and ii) an attention mechanism that identifies the importance of the measurement history in making risk predictions. This shared subnetwork predicts the next measurements of time-varying covariates. Using the context vector (the output of the shared subnetwork model) and the last measurements as input, the cause-specific subnetworks estimate the joint distribution of the first hitting time and competing events. Each cause-specific subnetwork employs a feed-forward network with fully connected layers to capture the relationship between the cause-specific risk and the measurements (context vector and last measurements). The output layer utilizes a softmax layer to generate an estimated joint distribution of the first hitting time and competing events.

Training the Dynamic-DeepHit model involves minimizing a total loss function that incorporates longitudinal measurements and accounts for right-censoring. The model utilizes both time-invariant and time-varying covariates, treating the survival time as discrete. Discretization is performed by transforming continuous-valued times into a set of contiguous time intervals. In the study by Lee et al. (2019), who introduced the Dynamic-DeepHit model, monthly data was retained, and the time was discretized with a resolution of one month.

Lee et al. (2019) developed a cause-specific time-dependent concordance index ($C_k(t;\Delta t)$) to assess the discriminative performance of various methods. This index is an extension of the time-dependent concordance index, proposed by Gerds et al. (2013. Lee et al, (2019) adapted this time-dependent concordance to the competing risks setting with longitudinal measurements. The ($C_k(t;\Delta t)$) index uses prediction and evaluation times to reflect possible changes in risk over time. The ($C_k(t;\Delta t)$) for event k is defined as;

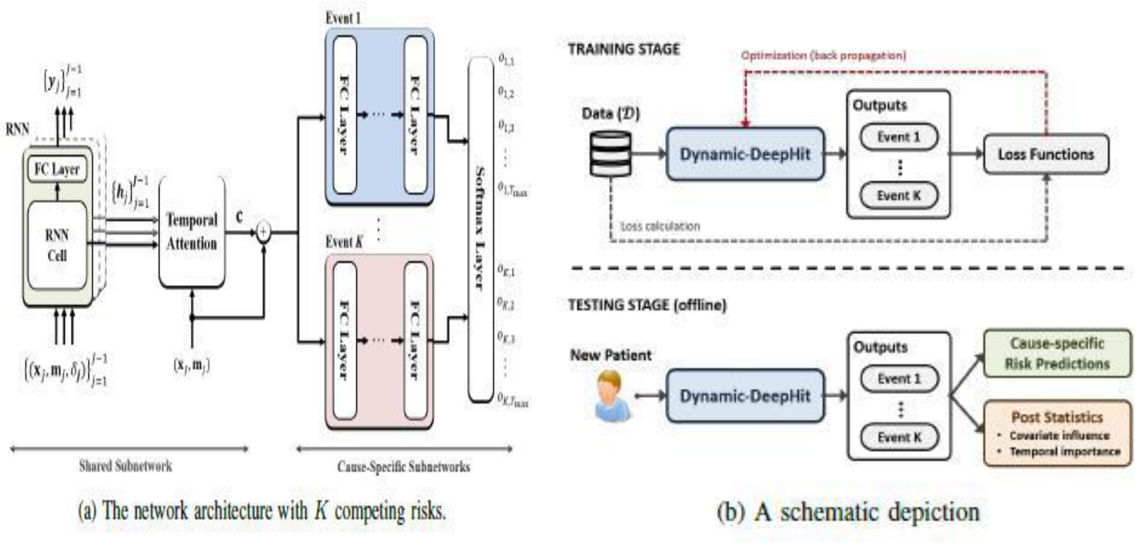
$$C_k(t;\Delta t) = P(\hat{F}_k(t+\Delta t|\chi^i(t)) > \hat{F}_k(t+\Delta t|\chi^j(t))|\tau^i < \tau^j, k^i = k, \tau^i < t+\Delta t), \quad (23)$$

where $\hat{F}_k(.)$ is the estimated CIF for cause k. t and Δt represent the prediction time and the evaluation time (time elapsed since the prediction is made), respectively. $\hat{F}_k(t + \Delta t|\chi^i(t))$ represents the predicted risk of event k occurring in Δt years by using the longitudinal measurements until t.

3.2.3. Deep Learning and Multi-State Model

Sirignano et al. (2018) investigated the transition of mortgages between 7 states (current, 30 days delinquent, 60 days delinquent, 90+ days delinquent, foreclosed, REO, and paid off) over its lifetime. A mortgage will transit between retained stated over its lifetime. These authors proposed to model the dynamic of the state process with a deep learning model; which is a nonlinear extension of the familiar logistic regression model. They used the empirical frequency of the different types of transitions between states and assumed that the dynamics of the state process be influenced by a vector of explanatory variables $X^n_t \in R^{dX}$. They modeled the marginal conditional probability for the transition.

Figure 2: Architecture of Dynamic DeepHit in case of 2 Competing Risk (Lee et al. (2019))



of the n-th mortgage from its state U^n_{t-1} at time t − 1 to state u at time t given the explanatory variables X^n_{t-1} as:

$$h_{\theta,l}(x) = g_l(W_l^T h_{\theta,l-1}(x) + b_l), \quad (24)$$

where $W \in R^K x R^{dK}$ and $b \in R^K$. l = 1, ...,L−1 where L−1 is the number of layer. The nonlinear transformation $g_l(z)$ is given by the softmax function defined as follows:

$$g(z) = (\frac{e^{z_1}}{\sum_{k=1}^{K} e^{z_k}}, ..., \frac{e^{z_K}}{\sum_{k=1}^{K} e^{z_k}}), \qquad z = (z_1, ..., z_K) \in R^K. \qquad (25)$$

The hidden nodes enable the nonlinear transformations of input variables (explanatory variables) and connect them to the output nodes (the conditional probabilities of the different mortgage states). The hidden nodes represent the nonlinear transformations of input variables.

At each layer l, the output $h_{\theta,l}(x)$ is a simple nonlinear link function g_l of a linear combination of the nonlinear basis functions $h_{\theta,l-1}(x)$, where the nonlinear basis function $h_{\theta,l-1}(x)$ must be learned from data via the parameter θ. The output $h_{\theta,l}(x)$ from the l-th layer of the neural network becomes the basis function for the (l + 1)-th layer.

Sirignano et al. (2018) investigated the explanatory power of explanatory variables by considering the behavior of the out-of-sample negative average loglikelihood $(\frac{1}{N} L_{T,N}(\hat{\theta}))$ with respect to changes of the set explanatory variables. This negative average loglikelihood is a standard measure of fit, called the cross-entropy error or simply the loss. The explanatory power of variables is measured by how much the loss increases when the variable is removed as an explanatory variable. A large increase in the loss means large explanatory power of the variable.

Regarding the economic significance of a particular variable on borrower behavior, it is measured by the magnitude of the derivative of a fitted transition probability with respect to the variable (averaged over the data). The sensitivity of the fitted probability with respect to j-th variable for a transition from state u to v is determined as:

$$E[|\frac{\partial}{\partial x_j} h_{\hat{\theta}}(V, X)|V = v, U = u].| \qquad (26)$$

A sensitivity of value a for a given variable means that the probability for a transition from state u to v will approximately change by zΔ if that variable is changed by a small amount Δ.

4. CONCLUSION

Effectively modelling prepayment and default risks is very important for assessing risk, valuing assets, making informed decisions, and ensuring the stability and profitability of financial institutions and markets. In the specific context of mortgage loans, the exercise of the prepayment option brings an end to the default option, and vice versa: competing risks. These competing risks are influenced by various factors. The impacts of these factors on these risks may not be simple, but complex.

Classical methods, such as classical survival models, model each risk separately without considering them as competing risks. Classical models like multi-state models and multinomial logit models have traditionally been used to model these competing risks. However, these models do not take into account possible complex responses of prepayment and default risk to their determinants. These complex influences of independent variables on considered risks are taken into account by recently proposed methods/models, such as the Random Survival Forest and Random Competing Risks Forests, as well as the DeepHit model and Dynamic DeepHit model.

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Appendix 1: Refinance Incentive

Ambrose and Sanders (2003) formalized the refinance incentive as follows:

$$PPOPTION(t) = \frac{r_c(t) - r_G(t)}{r_G(t)}$$

where r_c and r_G denote the contract interest rate at time t and the current 10-year Treasury rate at time t, respectively. The choice of this latter rate is due to the fact that new contracts are indexed to the 10-year Treasury rate.

Goodarzi et al., 1998): The PVR is expressed as:

$$RFI_{it} = \frac{\sum_{j=0}^{n} \frac{(cr_i - mr_{n,t})PP_i}{(1+d)^j}}{PP_i}100,$$

where I and R denote the note rate monthly and the current mortgage refinance rates on a monthly basis, respectively. M represents the remaining life of the loan in months.

Jacobs et al. (2005) determined the refinance incentive as follows:

$$RFI_{it} = \frac{\sum_{j=0}^{n} \frac{(cr_i - mr_{n,t})PP_i}{(1+d)^j}}{PP_i}100,$$

where "n" represents the number of months remaining until the next interest reset date, which is specific to the contract and changes over time. cr_i represents the contract interest rate, while $mr_{n;t}$ represents the market rate at time "t" for a loan with a duration of "n" months. Additionally, "d" represents the discount rate, assumed to be 3% annually. The loan amount, denoted as PPi" appears in both the numerator and denominator of the equation but is ultimately irrelevant to our measure of refinance incentive.

Elie et al. (2002) considered the average of the spread between the loan coupon rate and the market rate (δ(t)) from month t − 4 to month t − 7 in prepayment modelling. As Bennett et al. (1997), Elie et al. (2002) modelled the refinancing incentive as the exponential of the piecewise linear function $l(\bar{\delta})$, where l() is defined as:

$$\begin{aligned} l(\bar{\delta}(t)) &= exp[\alpha_1(\bar{\delta}(t) - u_1)^+ + \alpha_2(\bar{\delta}(t) - u_2)^+], \\ \bar{\delta}(t) &= \frac{1}{4}[\delta(t-4) + \delta(t-5)\delta(t-6)\delta(t-7), \end{aligned}$$

where the market interest rate is represented by the 10-year swap rate at time t.