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Determinants of Corporate Insolvency in Germany: An Empirical Analysis to Evaluate and Improve the Default Risk of Non-Financial Companies Listed in the CDAX

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Murcia, 10 de Febrero de 2021

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“There is no difference between science and art when it comes to creativeness, productiveness, to come to conclusions and to formulations.”

- Josef Albers (1968) -

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Resumen

Esta tesis contribuye al creciente cuerpo de literatura sobre insolvencias corporativas al desarrollar y aplicar una regresión semiparamétrica de riesgos proporcionales de Cox para covariables dependientes del tiempo con el fin de evaluar insolvencias de entidades no financieras incluidas en el índice bursátil CDAX alemán.

La literatura sobre inestabilidad y probabilidad de insolvencia (PD) se ha apoyado en una variedad de enfoques para evaluar la insolvencia, como por ejemplo el análisis multivariado, la regresión logística estática, la distancia al incumplimiento o modelos de riesgo. Independientemente de la metodología de investigación, la mayoría de los estudios empíricos se realizan predominantemente con datos de EEUU. Por lo tanto, existe una escasa contribución académica a la literatura alemana sobre PD. La presente es una de las primeras contribuciones en aplicar modelos de regresión de Cox comparativos exhaustivos fuera de la muestra utilizando el proceso de recuento de Andersen-Gill (AG-CP) basado en un conjunto de datos único de empresas no financieras con respecto al Estatuto de Insolvencia de Alemania. En este contexto, se emplea la importancia de los indicadores de alerta temprana para las insolvencias, como los ratios contables y financieros.

Los hallazgos sobre un mercado concreto (EEUU) no deben generalizarse necesariamente a otros países como Alemania. Por ello, el estudio propone un modelo de riesgos proporcionales de Cox con covariables dependientes del tiempo basadas en el conjunto predefinido de covariables seleccionadas. Se aplica un procedimiento de selección de variables escalonadas con iteraciones hacia adelante y hacia atrás para ajustar un modelo a medida para empresas no financieras en Alemania y para realizar pruebas fuera de la muestra.

Por otra parte, esta disertación evalúa el efecto de incluir variables de la industria para mejorar el poder discriminatorio y la precisión predictiva de los modelos ajustados. En la literatura científica actual se ha otorgado muy poca importancia al impacto en la industria. Según Chava y Jarrow (2004), los modelos de PD complementados con discriminaciones por industrias mejoran el poder predictivo de los modelos ajustados debido a los diferentes niveles de competencia entre las industrias, las convenciones contables específicas de la industria y los diferentes requisitos reglamentarios.

Finalmente, la muestra en la que se basa este estudio de doctorado está formada por empresas no financieras en activo e insolventes en el período 2000 a 2018, sujeto al inicio del primer estatuto concursal unificado en Alemania. Por lo tanto, este enfoque de muestreo permite informar resultados que no están sesgados por este importante cambio regulatorio de 1999. También examina los efectos de una ley que entró en vigor en 2012 para facilitar aún más la reestructuración de empresas (Gesetz zur weiteren Erleichterung der Sanierung von Unternehmen, conocido como "ESUG"). La introducción del ESUG no solo tiene como objetivo fortalecer los derechos de los acreedores, sino que también introdujo medidas para la apertura anticipada de procedimientos. En particular, se ha reforzado la autogestión, se han introducido procedimientos de protección y se ha simplificado el procedimiento del plan de insolvencia. Finalmente, esta disertación tiene como objetivo evaluar el impacto de la ESUG en las ratios de riesgo en el mercado de insolvencia alemán, ya que la evidencia empírica de este cambio legislativo es escasa.

Palabras clave: Predicción de insolvencia, Regresión de riesgos proporcionales de Cox, Selección de variables escalonadas, Área bajo la curva recursiva, análisis Walk-Forward

Abstract

This dissertation contributes to the growing body of literature by developing and applying a semiparametric Cox proportional hazards regression for time-dependent covariates to evaluate corporate insolvency for non-financial constituents represented in CDAX.

First, a comprehensive review of corporate distress and the probability of default (PD) literature shows that a variety of approaches have been used to assess corporate default have been applied, such as multivariate analysis, static logistic regression, distance-to-default, or hazard models. Irrespective of the methodology of related research, most empirical studies are predominantly conducted on U.S. data. Therefore, there is a sparse academic contribution to the German PD literature. This doctoral study is one of the first to apply thorough comparative out-of-sample Cox regression models using the Andersen-Gill counting process (AG-CP) based on a unique dataset of non-financial companies with respect to the German Insolvency Statute. In this context, the importance of early-warning indicators for insolvencies, such as accounting and financial ratios, are employed.

Second, prior findings for the U.S. must not necessarily be generalized to other countries like Germany. Therefore, the study promotes the best candidate for the final Cox's proportional hazards model with time-dependent covariates based on the predefined set of selected covariates. A stepwise variable selection procedure with forward and backward iterations steps is applied to fit a tailor-made model for non-financial companies in Germany and to perform out-of-sample tests.

Third, this dissertation evaluates the effect of including industry variables to improve the discriminatory power and predictive accuracy of fitted models. In the scientific literature to date, remarkably little importance has been attached to the impact on the industry.

According to Chava and Jarrow (2004), PD models supplemented by an industry grouping improve the discriminatory power of fitted models due to different levels of competition between industries, industry-specific accounting conventions as well as different regulatory requirements.

Finally, the sample on which this doctoral study is based consists of active and insolvent non-financial companies in the period 2000 to 2018, subject to the inception of the first unified insolvency statute in Germany. Hence, this sampling approach allows to report results which are not biased by this major regulatory change in 1999. It also examines the effects of a law that came into force in 2012 to further facilitate the restructuring of companies (Gesetz zur weiteren Erleichterung der Sanierung von Unternehmen, known as "ESUG"). The introduction of the ESUG not only aims at strengthening creditors' rights but also introduced measures for the early opening of proceedings. In particular, self-administration has been strengthened, protective shield proceedings introduced, and the insolvency plan procedure streamlined. Finally, this dissertation aims to evaluate the impact of the ESUG on hazard ratios in the German insolvency market since the empirical evidence for this legislative change is scarce.

Keywords: Insolvency prediction, Cox proportional hazards regression, Stepwise variable selection, Recursive AUC, Walk-forward analysis

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LIST OF ABBREVIATIONS

AG-CP	Andersen-Gill counting process
AktG	German Stock Corporation Act (*Aktiengesetz*)
AR	Accuracy rate
AUC	Area under the curve
BA	German Federal Employment Agency (*Bundesagentur für Arbeit*)
BCG	Boston Consulting Group
BCM	Business continuity management
BGH	German Federal Court of Justice (*Bundesgerichtshof*)
BIOST	Biostatistics
BMJV	Federal Ministry of Justice and Consumer Protection (*Bundesministerium der Justiz und für Verbraucherschutz*)
BSM-Prob.	Black–Scholes–Merton probability of bankruptcy
BV ESUG	Bundesverband ESUG und Sanierung Deutschland e.V.
CDAX	Composite DAX
CFI	Corporate Finance Institute
COVID-19	Coronavirus Disease 2019
COVInsAG	German COVID-19 Insolvency Suspension Act (*COVID-19-Insolvenzaussetzungsgesetz*)
DAX	German stock index (*Deutscher Aktien Index*)

DD	Distance-to-default
EBITDA	Earnings before interest, taxes, depreciation, and amortization
EGInsO	Introductory Act to the German Insolvency Statute (*Einführungsgesetz zur Insolvenzordnung*)
ERM	Enterprise risk management
ESUG	Law to further facilitate the restructuring of companies (*Gesetz zur weiteren Erleichterung der Sanierung von Unternehmen*)
EUR	Euro
FMStG	German Financial Market Stabilization Act (*Finanzmarktstabilisierungsgesetz*)
FPR	False-positive rate
GOF	Goodness-of-fit
HGB	German Commercial Code (*Handelsgesetzbuch*)
HgGUR	*Heidelberger gemeinnützige Gesellschaft für Unternehmensrestrukturierung mbH*
HRO	High-reliability organization
IDW	The German Institute of Certified Public Accountants (*Institut der Wirtschaftsprüfer in Deutschland e.V.)*
IDW S 11	Standard on the assessment of insolvency maturity (*Beurteilung des Vorliegens von Insolvenzeröffnungsgründen*)
IDW S 6	Standard on restructuring reports (*Anforderungen an Sanierungskonzepte*)
InsO	German Insolvency Act (*Insolvenzordnung*)

IOR	Inter-organizational relations
JUVE	*Verlag für juristische Information GmbH*
LDV	Limited dependent variable
M&A	Mergers and acquisitions
MDA	Multiple discriminant analysis
MLE	Maximum likelihood estimation
MoMiG	Law for the Modernization of the German Limited Liability Company Law and the Prevention of Misuse (*Gesetz zur Modernisierung des GmbH-Rechts und zur Bekämpfung von Missbräuchen*)
OBO	Organizational burnout
OLS	Ordinary least squares
PCE	Piecewise constant exponential model
PD	Probability of default
PH	Proportional hazard
PL	Partial likelihood
R&D	Research and development
RegE	Draft bill (*Regierungsentwurf*)
ROA	Return on total assets
ROC	Receiver operating characteristics
ROE	Return on equity
ROI	Return on investment

SIC	Standard industrial classification
SLE	Significance level for entry
SLS	Significance level for stay
SME	Small and medium-sized enterprise
TDS	Thomson Reuters Datastream
TPR	True-positive rate
U.K.	United Kingdom
U.S.	United States of America
USD	United States Dollar
VOF	Variance inflating factor

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LIST OF SYMBOLS

α	Alpha
$ACTIVITY$	Status indicator in TDS distinguishing between $ACTIVE$ and $DEAD$ firms
AP	Accounts payable
AR	Accounts receivable
$BE_{adjusted\ i,t}$	Adjusted book value of equity for i at t
β	Regression coefficient
c_j	Number of censored observations for interval *j*
C	Cut-off threshold
CA	Current assets
$CASH$	Cash & short-term investments
CF	Cash flow
$CHIN$	Change in net income
CL	Current liabilities
$cluster(IDENT)$	Cluster variance for company identification
$\chi 2$	Chi-square test
d_j	Number of defaults for interval *j*
D	Debt
df	Degrees of freedom

δ	Interval
η_i	Logit transformation
E	Equity
$EBIT$	Earnings before interest and taxes
$EBITDA$	Earnings before interest, taxes, depreciation, and amortization
$ESUG$	Dichotomous variable that takes the value 0 for i at t before $ESUG$ entered into force and 1 after the inception of $ESUG$ in 2012
$\exp(x_i\beta)$	Relative risk function
$EXRET$	Past excess return calculated as a firm's past excess return in year $t\ -1$ minus the value-weighted CDAX benchmark index return in year $t\ -1$
$EXRETAVG$	Average past excess return calculated as a stock excess return against the CDAX while applying geometrically declining weights and $\emptyset = 2^{-\frac{1}{3}}$
FU	Funds provided by operations
$\hat{h}(t)$	Nelson-Aalen estimator
$h(t)$	Hazard function
$\boldsymbol{H_a}$	Alternative hypothesis
$h_0(t)$	Baseline hazard function
i	Firm
$iauc$	Integral of AUC on [1,19] weighted by the estimated probability density of the time-to-event outcome
ICR	Interest coverage ratio

IND	Categorial grouping according to the four-digit SIC code
$INTWO$	One if net income was negative for the last two years zero otherwise
INV	Inventory
$\mathcal{L}(\beta)$	Log-likelihood function
lI	Lower 95% confidence interval
MB	Market-to-book ratio
ME	Market value of equity
MTA	Equity component of total assets at market value by adding the book value of liabilities to the market value of equities
n_j	Number at risk for interval j
n	Number of observations
$NAME$	Security type in TDS
NI	Net income
O	O-Score
$OENEG$	One if total liabilities exceed total assets zero otherwise
OI	Operating income
π_i	Probability in the logit model
$\emptyset$	Phi
p	P-value
$pf/pref$	Preferred stock

$PRICE$	End of period log price per share of the firm truncated above EUR 15
RE	Retained earnings
$RSIZE$	Relative size calculated as the natural logarithm of each firm's market capitalization at the end of the year before the observation year relative to the total size of CDAX
$\boldsymbol{RQ}$	Research question
R^2	R-squared
$\hat{S}(t_j)$	Survival function for a given time interval t_j
$\hat{S}(t)$	Kaplan-Meier estimator
S	Sales
$S(t)$	Survival function
SE	Standard error
$SEGN$	Segments in TDS
$SIGMA$	Annualized standard deviation of the residual of a daily regression against the benchmark index CDAX
$SIZE$	Logarithm of total assets divided by the price-level index
t_j	Ranked time interval
t	Time
TA	Total assets
TC	Total capital
TL	Total liabilities

τi	Maximum potential observation time for $i = 1, \ldots, n$
uI	Upper 95% confidence interval
WC	Working capital
x_i	Observed covariates for i
$\mathbf{X}$	Set of explanatory variables denoted by the bold $\mathbf{X} = (X_1, X_2, \ldots, X_p)$
$\mathbf{X}(t)$	Set of time-independent explanatory variables $\mathbf{X}(t) = (X_1, X_2, \ldots, X_{p1})$, denoted by X_i, and time-dependent explanatory variables $\mathbf{X}(t) = \left(X_1(t), X_2(t), \ldots, X_{p2}(t)\right)$ denoted by $X_j(t)$
Y_i	Binary dependent variable for i
$YEAR$	Continuous variable.accounting for varying insolvency rates for the given time span.
Z	Z-Score

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1 INTRODUCTION

> "[Marginal companies] have lost market value because of poor performance, they are inefficient producers, and they are likely to have high financial leverage and cash flow problems. They are marginal in the sense that their prices tend to be more sensitive to changes in the economy, and they are less likely to survive adverse economic conditions" (Chan and Chen, 1991, p. 1468).

1.1 PROBLEM DESCRIPTION

Research interest in the context of corporate insolvencies is not limited to academics since every insolvency case has far-reaching consequences (Ohlson, 1980, p. 111). Indeed, every corporate insolvency case does not only directly affect its various groups of shareholders, but also has a negative impact on a wide range of stakeholders involved, from investors, managers, employees, customers, and suppliers as well as companies linked in its supply chain, to the economy and society (Jackson and Wood, 2013, p. 184). Although insolvency is a relatively rare event among listed companies in Germany, an understanding of its characteristics compared with other legal forms shown in Figure 1.1 is essential, not only for academics but also for managers (Creditreform Wirtschaftsforschung, 2019, pp. 8–9). According to the German Stock Corporation Act (*Aktiengesetz*, hereinafter referred to as "AktG"), "the management board shall take suitable measures in particular surveillance measures to ensure that developments threatening the continuation of the company are detected in processes at an early stage" (*Aktiengesetz (AktG), 2020*, Sec. 91 (2)).

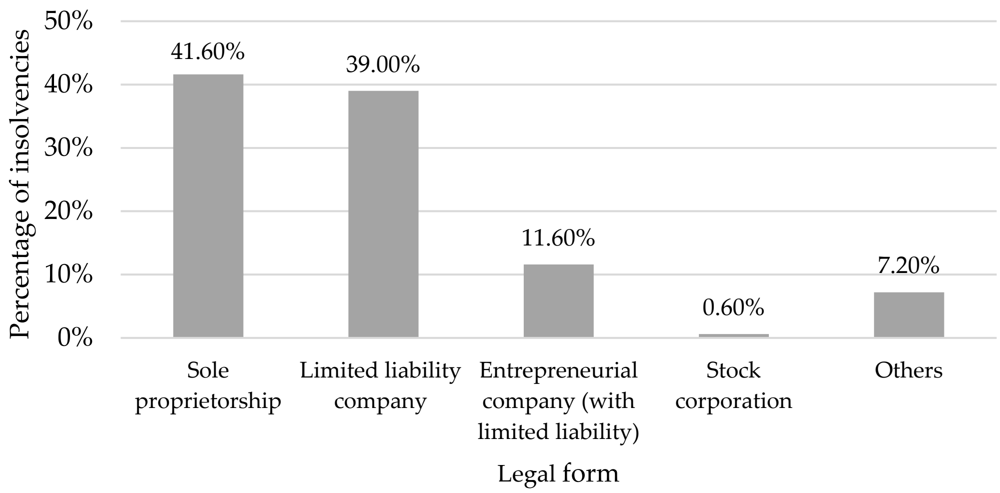

Figure 1.1: German corporate insolvencies breakdown by legal form in 2019

[Source: Author's representation based on CRIF Bürgel GmbH (2020)]

At first glance, only 0.6% of corporate insolvencies in 2019 are attributable to the stock corporation. Nonetheless, this relatively small distribution is of great importance for academic research purposes, as regulated public companies offer a transparent range of accounting-based, financial and macroeconomic indicators such as cash to total assets ($CASHTA$), net income divided by the market value of debt ($NIMTA$), or relative size to an index ($RSIZE$) (Campbell, Hilscher, and Szilagyi, 2008, p. 2907).

Although the prediction of corporate insolvencies and the assessment of corporate default risk has been the subject of much academic research in recent decades (Altman, 1968; Ohlson, 1980; Shumway, 2001; Campbell, Hilscher, and Szilagyi, 2008; Mertens, Poddig, and Fieberg, 2018), a significant research contribution has been devoted to U.S. samples. From this literature, competing empirical models with manifold explanatory variables and alternative statistical methods for model estimation have evolved. However, the relevant research on German samples using state-of-the-art empirical approaches is limited as presented in the comprehensive literature review in Chapter 4.1. Therefore, this dissertation aims to fill this research gap and forecasts corporate insolvency by using an enhanced *Cox proportional hazards regression model* with explanatory variables constructed from *accounting*, *market-based* ratios and other variables, such as *industry grouping* and *legislative changes*. A reliable data source is a key element for sound empirical results. The German Composite Dax (CDAX) therefore serves as a suitable proxy for analyzing the determinants and characteristics of German insolvencies, especially for non-financial listed companies.

1.2 OBJECTIVES

This dissertation contributes to the growing body of literature by applying and testing semiparametric Cox proportional hazards regression models for time-dependent covariates to evaluate corporate insolvency for non-financial constituents represented in CDAX.[1]

First, a comprehensive review of corporate distress and the PD literature shows that a variety of approaches have been applied to assess corporate default, such as multivariate analysis, static logistic regression, distance-to-default, or hazard models (Altman, 1968; Ohlson, 1980; Shumway, 2001; Campbell, Hilscher, and Szilagyi, 2008; Mertens, Poddig, and Fieberg, 2018). Irrespective of the methodology of related research, most empirical studies are predominantly conducted on U.S. data.[2] Therefore, there is a sparse academic contribution to the German PD literature. This dissertation is among the first to apply out-of-sample Cox regression using the Andersen-Gill counting process (AG-CP) on the basis of a unique database of non-financial companies with regard to the German

[1] Partial results of the presented work have been published in: Ledwon, A. V. and Jäger, C. C. (2020) "Cox Proportional Hazards Regression Analysis to assess Default Risk of German-listed Companies with Industry Grouping", *ACRN Journal of Finance and Risk Perspectives*, 9(1), pp. 57–77. doi: 10.35944/jofrp.2020.9.1.005.

[2] For a detailed review of methodologies applied to assess corporate default, see Chapter 4.1.

Insolvency Statute. In this context, early-warning indicators for insolvencies, such as accounting-based ratios and market-based indicators, are employed.

Second, prior findings for the U.S. must not necessarily be generalized to other countries like Germany. Therefore, this dissertation promotes the best candidate for the final Cox's proportional hazards model with time-dependent covariates based on the predefined set of selected covariates.[3] A stepwise variable selection procedure with forward and backward iterations steps is applied to fit a tailor-made model for non-financial companies in Germany and to perform out-of-sample tests.

Third, this dissertation evaluates the effect of including industry variables to improve the discriminatory power and predictive accuracy of fitted models. In the scientific literature to date, remarkably little importance has been attached to the impact on the industry. According to Chava and Jarrow (2004), PD models supplemented by an industry grouping improve the discriminatory power of fitted models due to different levels of competition between industries, industry-specific accounting conventions as well as different regulatory requirements.

Finally, the sample on which this dissertation is based consists of active and insolvent non-financial companies in the period from 2000 to 2018, subject to the inception of the first unified insolvency statute in Germany. Hence, this sampling approach "allows to report results which are not biased by this major regulatory change in 1999" (Ledwon and Jäger, 2020, p. 75). It also examines the effects of a law that came into force in 2012 to further facilitate the restructuring of companies (Gesetz zur weiteren Erleichterung der Sanierung von Unternehmen, known as "ESUG"). The introduction of the ESUG not only aims at strengthening creditors' rights but also introduced measures for the early opening of proceedings. In particular, "self-administration has been strengthened, protective shield proceedings introduced, and the insolvency plan procedure streamlined" (Moraht and Lütcke, 2012). Finally, this dissertation aims to evaluate the impact of the

[3] For a detailed review of the stepwise variable selection to compute a best candidate model fit, see Chapter 5.3.2.

ESUG on hazard ratios in the German insolvency market since the empirical evidence for this legislative change is scarce.

In view of the fact that there is no coherent scientific consensus within the probability of default (PD) literature about the determinants and characteristics of corporate insolvencies in Germany, the general objective of this dissertation is to answer the following research questions:

RQ1: *Do market-based predictors provide superior empirical results in terms of discriminatory power and accuracy rates when compared to a parsimonious accounting-based approach and a hybrid variable selection?*

RQ2: *Does the stepwise variable selection procedure for Cox's proportional hazards regression model with forward and backward iteration steps statistically improve the discriminatory power and accuracy rates of the fitted PD models?*

RQ3: *Does the inclusion of a categorial industry grouping according to the four-digit SIC statistically improve discriminatory power and forecasting accuracy of fitted PD models?*

RQ4: *Are companies that implement ESUG measures according to InsO Sections 270a and 270b statistically associated with a healthier financial situation, ceteris paribus, prior to filing for insolvency?*

1.3 SCOPE OF WORK

The dissertation is divided into six chapters. Chapter 1 summarizes the research topic, its relevance to academic research and corporate risk management, and presents the research objectives of the thesis.

The second chapter focuses on corporate crises and delimits crisis-related terminologies to allow a common understanding of the concept. The theoretical four-phase models according to Krystek (1987) and Müller (1982) are used to enable a better understanding of the factors influencing the crises and the measures of crisis management. The current state of empirical research on the causes of corporate crises is presented in Chapter 2.3 to show their limitations. A presentation of reactive and proactive approaches as well as research on organizational or inter-organizational crisis management complements this key management concern. For the purposes of this dissertation, the concept of corporate restructuring is introduced in order to provide a theoretical basis for phases preceding insolvency. In this context, the recently streamlined IDW S 6 is presented, which explains out-of-court restructuring for companies in distress as a reactive approach to overcoming corporate crises and ensuring the continued existence of an organization.

In the third chapter, the theoretical foundation of corporate insolvencies is laid, which is one of the core elements of this dissertation. The development of a PD model for German-listed companies requires a concise definition of corporate failure in order to ensure the robustness and consistency of the empirical findings. A comprehensive literature review should be conducted with a narrow definition of financial distress and its relationship to specific events such as insolvency proceedings. Thus, a consistent definition of the event variable should be developed. A delimitation and definition of corporate crises and corporate insolvencies are therefore indispensable for the objectives of this dissertation. In accordance with current literature, this dissertation defines the concept of insolvency according to the national statute InsO (*Insolvenzordnung*, hereinafter referred to as "InsO"). Against the background of the current legal environment, the recent legislative extension of InsO, namely the law to further facilitate the restructuring of companies (*Gesetz zur weiteren Erleichterung der Sanierung von Unternehmen*, hereinafter referred to as "ESUG") (Moldenhauer and Wolf, 2017, p. 2) and its measures are introduced.

The fourth chapter summarizes a wide range of approaches to modeling corporate failures. Subsequently, a systematic derivation of the applied research method is presented. After a short introduction to logit models for binary data in Chapter 4.2, a theoretical discussion on survival analysis is presented. In particular, non-parametric, parametric approaches, and semiparametric regression models on survival data are highlighted. As a result, the enhanced Cox proportional hazards regression, taking into account the AG-CP, is selected as a promising tool for the evaluation and estimation of determinants of corporate insolvency for non-financial constituents in the CDAX. Chapter 4.4 presents model diagnostics and goodness-of-fit measures that can be used to determine whether fitted Cox regression models adequately describe the empirical results presented. With regard to the validation criteria, discriminatory power is assessed by performing dynamic AUC for right-censored time-to-event data as proposed by Chambless and Diao (2006). As far as model calibration is concerned, this dissertation computes walk-forward tests. This rigorous out-of-sample out-of-time procedure is proposed by Sobehart, Keenan, and Stein (2000).

The fifth chapter presents the empirical analysis. The formulated research questions are translated into seven measurable theory-based hypotheses. The adjusted data and descriptive statistics, such as insolvency rates, industry breakdowns, and non-parametric analysis, are presented in Chapter 5.2. The empirical analysis shows in-sample empirical results of hazard ratios and out-of-sample measures to assess the discriminatory power and forecast accuracy of fitted PD models, which are discussed and supplemented by a benchmark analysis.

Finally, the sixth and last chapter concludes the dissertation by summarizing the most important empirical findings and proposing further related and fruitful areas for subsequent research. Figure 1.2 gives an overview of the structure of the thesis; arrows indicate how the sections are combined to investigate the topic of the thesis.

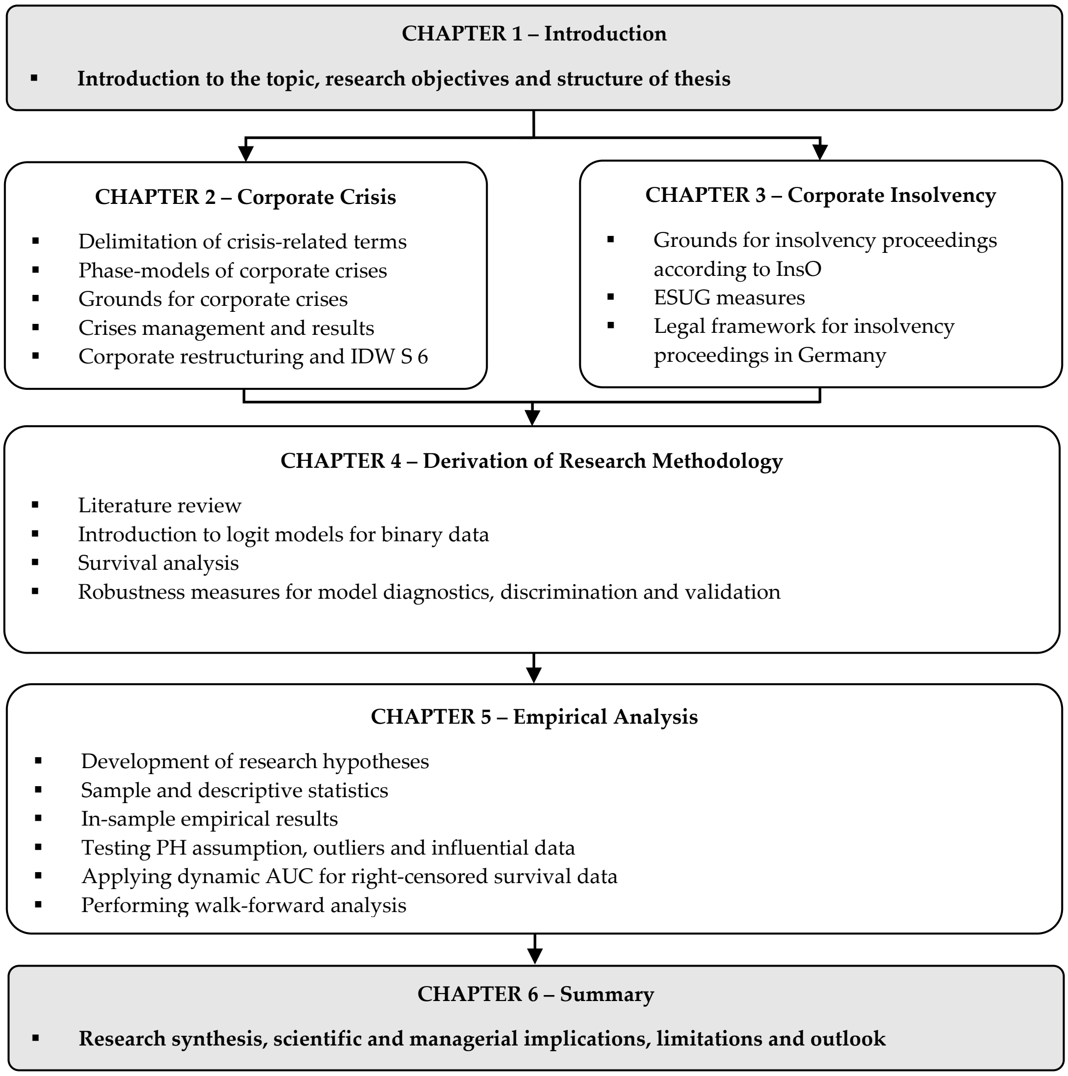

Figure 1.2: Structure of the dissertation

[Source: Author’s representation]

2 CORPORATE CRISES

In view of the recent financial crises in the U.S. and Europe, the term *crisis* has been used in an almost inflationary way (Krystek and Lentz, 2013, p. 29). A delimitation and definition of a corporate crisis is therefore indispensable for the objectives of this dissertation. In business administration, a corporate crisis is an event or series of events with unknown outcome that threatens the ability of a company to operate its business effectively (Drukarczyk and Schöntag, 2020, n. 2). In this context, the achievement of traditional corporate goals is jeopardized, which leads to the threat of value destruction or the continued existence of a company (Krystek, 1987, pp. 6–7). An in-depth definition of corporate crises is influenced by various factors. Krystek (1987) groups the definitions between scientific disciplines to provide a diversified picture of this terminology. In particular, Krystek (1987) associates corporate crises with an existential threat, ambivalent outcomes, failure to achieve dominant goals, a complex decision-making environment as well as a process perspective with regard to controlling and leadership, as defined below (Krystek, 1987, p. 6).

(1) *Existential threat*: A corporate crisis is an unplanned and unintended event that can lead to a cessation of business (Krystek, 1987, p. 6).
(2) *Ambivalent outcomes*: On the one hand, a corporate crisis can lead to the discontinuation of business operations and formal liquidation, on the other hand, it offers the opportunity to restructure the company (Krystek, 1987, p. 6).
(3) *Non-achievement of the dominant objectives*: A corporate crisis can be quantified as soon as dominant corporate goals, such as measurable financial goals like liquidity or profitability, are not achieved (Krystek, 1987, p. 6).
(4) *Process perspective*: The onset of a corporate crisis, which is initially identified by management and depends mainly on measures for early crisis identification (Krystek, 1987, p. 6).

In view of ambivalence of the outcome mentioned above, Groß (1988) defines a corporate crisis as an emergency situation that can be solved by restructuring the target company and that offers the possibility of survival or liquidation of the company after an application for insolvency has been filed (Groß, 1988, p. 4). In addition to the determinants of corporate crises already mentioned, the factors time and decision-making are central features of corporate crises in the context of crisis management (Portisch, 2005, p. 9). As a result, corporate crises can be defined as a large and complex challenge that must be overcome in order to ensure the long-term survival and success of a company (Kraus and Haghani, 2004, p. 14).

In this chapter, crisis-related terms such as catastrophes, conflicts, disruptions, organizational burnout, risk, or trends are delimited in order to allow a more in-depth definition of corporate crisis. After the delimitation of crisis-related terms, classifications of corporate crises are discussed. In this regard, corporate crises can be assessed from a process approach or explained by crisis symptoms due to internal and exogenous factors.

The academic literature on phase models for corporate crises is manifold. Britt (1973), Röthig (1976), Rödl (1979) and v. Löhneysen (1982) have inter alia proposed approaches which laid foundation for further academic contribution by Krystek (1987) and Müller (1982). In this context, the four-phase models according to Krystek (1987) and Müller (1982) are considered suitable approaches, as each allows a profound and granular discussion on influencing crisis factors, measures for crisis management, and forms of corporate restructuring as outlined in Chapter 2.2.

Subsequently, reasons for corporate crises are dissected, and evidence of German insolvency cases is presented. A brief discussion of qualitative and quantitative approaches concludes Chapter 2.3. The latest research findings on crisis management, divided into organizational and inter-organizational crisis management, will be presented to raise awareness of proactive and reactive approaches and their potential outcomes. Finally, the forms of corporate restructuring as part of successful crisis management are discussed in the light of the most recent changes in restructuring concepts, namely the streamlined IDW S 6. Figure 2.1 summarizes the course of the reasons for the corporate crises highlighted above and their effects on the continued existence of a company. Corporate insolvencies are examined separately in Chapter 3.

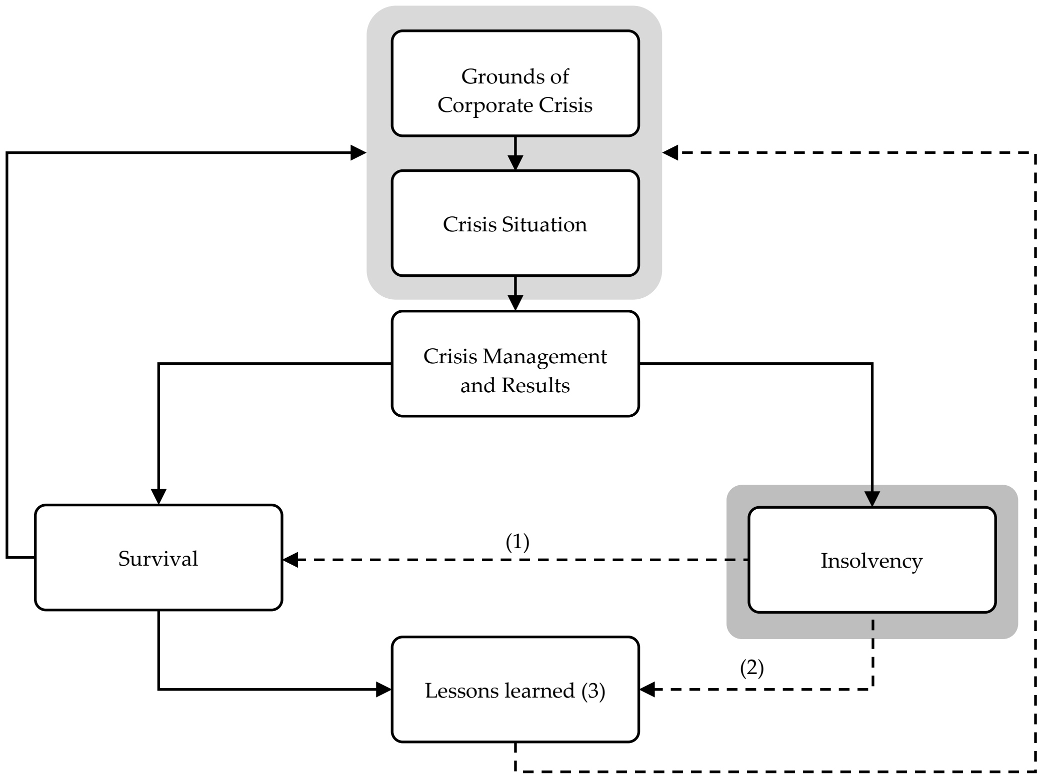

Figure 2.1: Flowchart corporate crisis

[Source: Author's representation]

2.1 DELIMITATION OF CRISIS-RELATED TERMS

With special regards to English literature, the term crisis is frequently related to aspects of *risk* and or *disaster* (Smith and Elliott, 2006, pp. 7-12). Nonetheless, Pearson and Clair (1998) filled this research gap by providing a clear and valuable definition of organizational crisis and crisis management. According to Pearson and Clair (1998), a crisis is "a low-probability, high-impact event that threatens the viability of the organization and is characterized by ambiguity of cause, effect, and means of resolution, as well as by a belief that decisions must be made swiftly" (Pearson and Clair, 1998, p. 60). Considering the aforementioned definitions of corporate crisis, a delimitation of crisis-related terms is indispensable. Figure 2.2 underlines certain overlaps between corporate crisis and crisis-related terms (Michalak, 2012, p. 29ff.).

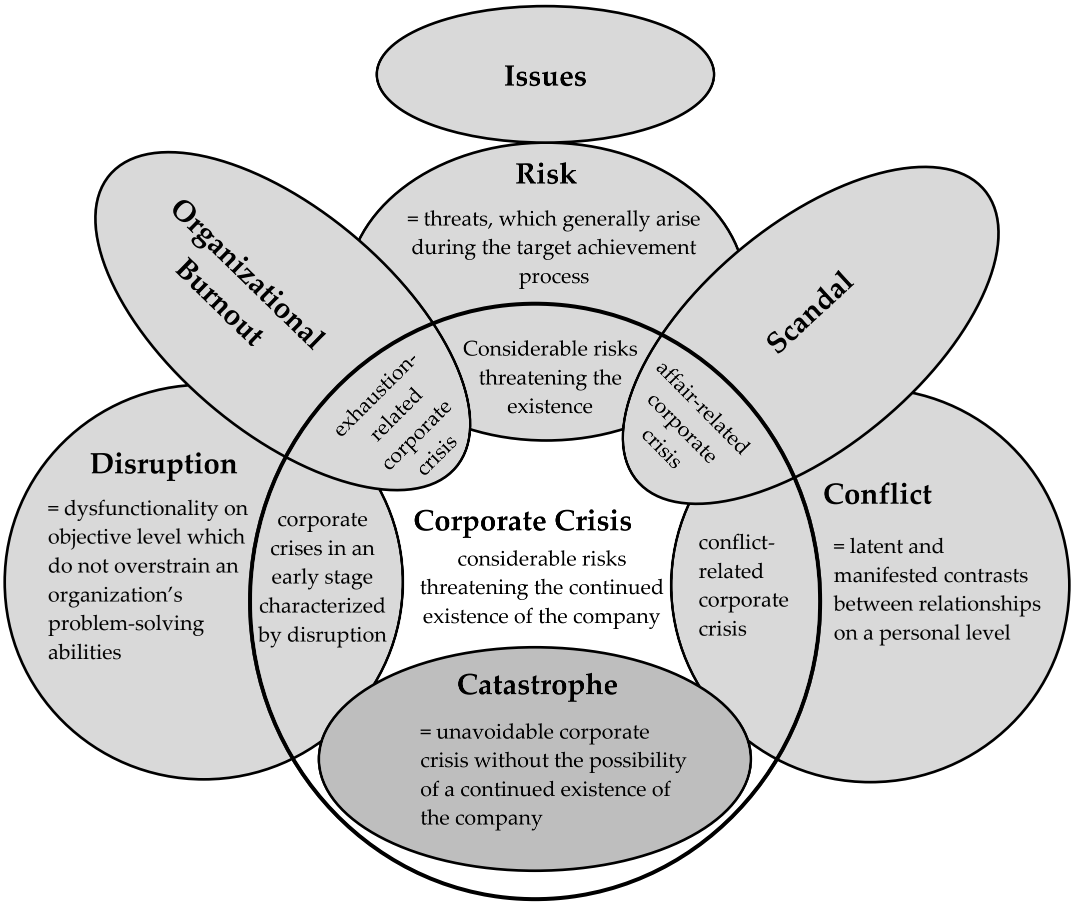

Figure 2.2: Delimitation of terminologies referring to corporate crises

[Source: Author's representation based on Krystek and Lentz (2013, p. 33)]

Catastrophes describe a special situation within corporate crises that are characterized by negative attributes that hinder the survival of a company (Michalak, 2012, p. 32f.). In other words, it can be defined as inevitable corporate crises without any chance of rescue or survival. In the context of vulnerability analysis, disruptions indicate dysfunctionality at the operational level, which leads to decreasing efficiency (Baetge, Schmidt, and Hater, 2016, p. 21). The destructive power of disruptions can trigger critical processes that lead to a catastrophe (Krystek, 1987, p. 9). Unlike disruptions, conflicts are defined as covert and manifest opposites on a personal level, which on one hand, can promote problem-solving skills, also known as constructive conflicts (Dahrendorf, 1961, p. 201f.) On the other hand, one can distinguish between conflicts that are characterized by destructive effects, which often become visible in power struggles between managers, employees, and other shareholders, or stakeholders (Michalak, 2012, p. 31f.). Risks are an inseparable element of corporate actions and offer the chance of corporate success (Krystek and Lentz, 2013, p. 33). Risks can therefore be defined as threats arising from the process of achieving objectives and can be distinguished from risks that jeopardize the continued existence of a company (Krystek and Moldenhauer, 2007, p. 28). According to Heath and Palenchar (2009), an issue is "a contestable point, a difference of opinion regarding fact, value, or policy, the resolution of which has consequences for the organisation's strategic plan and future success or failure" (Heath and Palenchar, 2009, p. 93). Thus, the term issue is linked to trends and stakeholder interests, and if not strategically anticipated, issues can lead to a corporate crisis at a later stage, as Henry Kissinger emphasized: "An issue ignored is a crisis ensured" (quoted from Regester, 2013, p. 159). The occurrence of sudden and unpredictable affect-related disruptions in the public sphere defines a scandal, as there is a clear evaluation of values and norms (Krystek and Moldenhauer, 2007, p. 31). Recent examples of corporate scandals are the Volkswagen emissions scandal, also known as *Dieselgate*, which led to a serious corporate crisis in 2015 (Marcus and Hargrave, 2020, Chap. 10) and the recent *Wirecard scandal* in 2020 which was linked to a series of accounting scandals that finally resulted in the insolvency of Wirecard AG, a former German payment provider and financial services company that was part of the DAX (McCrum, 2020). A contemporary crisis-related term according to Greve (2010) is Organizational Burnout (OBO). This crisis-related phenomenon affects mature companies with an average capacity for innovation and leads to an exhausted and paralyzed state of a company (Greve, 2010, pp. 20, 46ff.). The reason for the appearance of OBO is failures in management, which have demotivating effects on the employees involved (Greve, 2010, p. 46ff.).

2.2 PHASE-MODELS OF CORPORATE CRISES

After defining crisis-related terms, the following sections discuss the causes and phases for corporate crises according to Krystek (1987) and Müller (1982).[4] The reasons for corporate crises may be explained by crisis symptoms, which can be distinguished between internal and exogenous crisis symptoms. Corporate crises can be assessed from a process approach of influenceability and controllability of a company. In this context, the four-phase model according to Krystek (1987) is presented, which allows a better understanding of influencing crisis factors and measures for crisis management. In addition, the four-phases model according to Müller (1982) is presented, which decomposes and translates corporate crises as phases that jeopardize corporate objectives (Müller, 1982, pp. 25–27).

2.2.1 Four-phase-model according to Krystek (1987)

With reference to the principle of influence and control, Krystek (1987) proposed a four-phase model, which is based on earlier scientific work by Britt (1973), Röthig (1976), Rödl (1979), v. Löhneysen (1982), and Müller (1982). According to Krystek (1987), corporate crises go through several developmental phases: potential, latent, and acute crises as shown in Figure 2.3. It is important to note that the phase model presented follows an ideal type of sequenced crisis process. Krystek (1987) emphasizes that organizations do not necessarily go through all four phases in sequential order. Therefore, corporate crises can evolve in one of the mature phases, and companies may fall back into less destructive phases (Krystek, 1987, p. 32).

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[4] The four-phase models according to Krystek (1987) and Müller (1982) have been selected as both approaches show substantial congruity with the six crisis stages defined in IDW S 6, see Chapter 2.5.2.

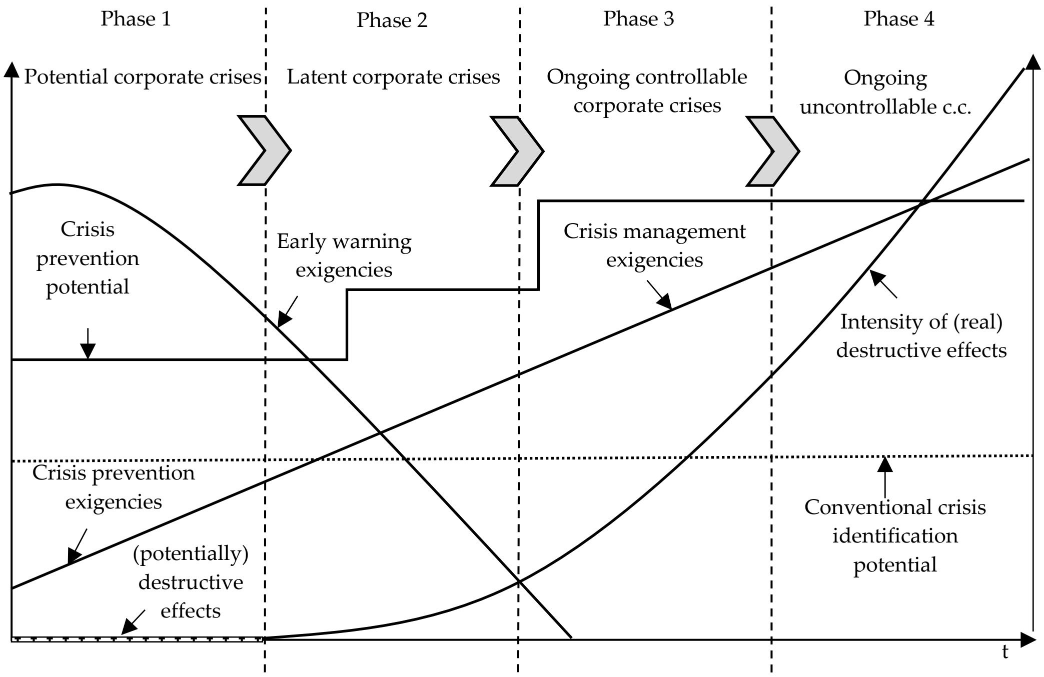

Figure 2.3: Four-phase model according to Krystek (1987)
[Source: Author's representation based on Krystek (1987, p. 30)]

By definition, Phase 1 indicates the starting point of any corporate crisis, which is referred to as a potential corporate crisis, where the organization is operating in a quasi-normal state and therefore no reasonable signs of a crisis are apparent (Krystek, 1987, pp. 29–30). In other words, the performance of a company may be jeopardized by potential endogenous and exogenous threats that require early management action (Britt, 1973, p. 438; v. Lohneysen, 1982, p. 104). Early management action makes it possible to derive measures to reduce crisis prevention exigencies in good time, whereby the identification of individual, relevant corporate crises is particularly difficult (Krystek, 1987, pp. 29–30).

In a second stage, latent corporate crises mark the subsequent phase. If no appropriate measures are introduced during the potential crisis, difficulties in achieving strategic goals can be the first indicators of a latent crisis (Krystek, 1987, p. 30). Although the likelihood of a corporate crisis is higher, an early warning system and the potential for crisis detection are still not fully realized (Krystek, 1987, p. 31). Nonetheless, efforts of early detection of the hidden latent crisis should be intensified, as there is still room for maneuver and immediate measures can be implemented without coercion (Krystek, 1987, p. 31). Since the potential corporate crisis is focused on the time of crisis origin, when the organization is still in a quasi-normal state, the latent corporate crisis is defined by a hidden crisis that is likely to be approached (Krystek, 1987, pp. 29–31).

The third stage introduces the open corporate crisis, also known as evident or acute crises when previous measures were taken during potential and latent crises that proved to be unfulfilled (Krystek, 1987, p. 31). This stage is characterized by an obvious threat to the operational performance of a company and can be distinguished between a sustained controllable corporate crisis and a subsequent uncontrollable corporate crisis (Krystek, 1987, p. 31). A persistent, controllable crisis begins with the perception of the destructive power of a crisis and therefore instruments for early crisis prevention are superfluous (v. Lohneysen, 1982, p. 104). This increases the intensity of the real destructive effects, which leads to time pressure (Müller, 1982, p. 25) accompanied by immediate and urgent management decisions (Krystek, 1987, p. 31). As a result, the demands on crisis management are high since at the same time the scope for countermeasures decreases (Röthig, 1976, pp. 13–15). Crisis management resources are pooled to solve the actual crisis. However, an accumulation of crisis management activities can even accelerate the crisis development process if resources are not utilized efficiently and intensified actions send the wrong signals (Krystek, 1987, p. 31). It can be formulated that a negative impact of the crisis occurs, as counteractions may not lead to the overcoming of an actual crisis. Finally, the organization is still in a state of crisis management, as there is room for the controllability of the crisis (Krystek, 1987, p. 31).

According to Krystek (1987), persistent uncontrollable corporate crises represent the fourth and last stage of the crisis process. From the perspective of an organization, the current crisis leads to a catastrophe (Krystek, 1987, p. 9), which can become visible by the failure to achieve important company goals, such as liquidity (Britt, 1973, p. 439). This phase is visually illustrated in Figure 2.3, where the intensity of the real destructive effects overlaps with the requirements of crisis prevention measures. At this stage, management tries to mitigate with improvised influence to overcome the destructive effects, but increasing time pressure and managerial actions limit such actions (Krystek, 1987, p. 31).

2.2.2 Four-phase model according to Müller (1982)

Müller (1982) categorizes crisis stages according to endangering corporate objectives and uses a four-phase model that takes the time factor into account (Müller, 1982, pp. 25–27). The four phases are (1) strategic crisis, (2) profitability crisis, (3) liquidity crisis, and finally, (4a) insolvency proceeding and/or (4b) liquidation as shown in Figure 2.4. In particular strategic crises (1) occur when maintaining the competitive advantage and strategic long-term goals of an organization are at risk. In this stage, the severity of the crisis is low. The scope of action therefore allows the formulation of long-term countermeasures to prevent entry into subsequent phases (Müller, 1982, pp. 25–27). Consequently, the profitability crisis (2) arises as quantifiable profitability indicators decline such as return on assets (ROA), return on investment (ROI), and return on equity (ROE) (Müller, 1982, pp. 25–27). Next, the liquidity crisis (3) manifests itself as the beginning of a severe crisis environment, as the company is not able to pay its due liabilities and thus falls into a state of illiquidity (*Insolvenzordnung (InsO)*, 2020, Sec. 17). A detailed analysis of illiquidity is provided in Chapter 3. According to Müller (1982), filing for insolvency (4a) marks the final phase in which a company loses the remaining room for maneuver, as it is placed under the applicable insolvency law in order to enable creditor's claims to be satisfied equally by liquidating the debtor's assets (Müller, 1982, pp. 25–27; Hofmann and Giancristofano, 2018). The last stage of Müller (1982) describes the liquidation (4b) of a company.

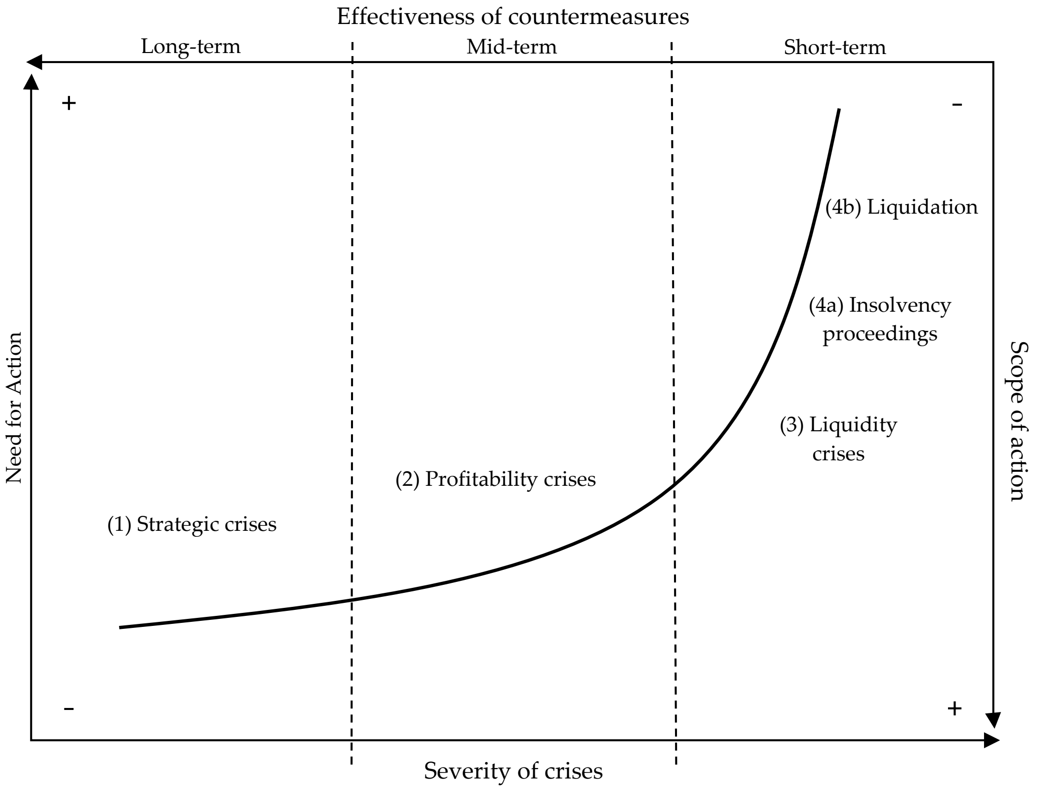

Figure 2.4: Four-phase model according to Müller (1982)

[Source: Author's representation based on Müller (1982, p. 27)]

2.3 REASONS FOR CORPORATE CRISES

With regard to the reasons for corporate crises, a distinction may be made between quantitative and qualitative research approaches. Quantitative research on reasons for corporate crisis includes the descriptive evaluation of measurable indicators of insolvent companies, such as industry, size, age, to trace the roots of the corporate crisis (Krystek and Lentz, 2013, p. 34f.; Behringer, 2017, pp. 26–33; Creditreform Wirtschaftsforschung, 2019).[5] In contrast, qualitative research on reasons for corporate crisis draws attention to expert opinions of companies that

[5] A systematic literature review of the development and improvements on various quantitative methodological approaches to bankruptcy forecasting has to be delimited from descriptive quantitative research and is provided in Chapter 4.1.

are in a stage of entering a corporate crisis in order to provide practical recommendations derived from surveys or current news (Hauschildt, Grape and Schindler, 2006; Krystek and Moldenhauer, 2007, p. 41; Behringer, 2017, pp. 23–26). Irrespective of the research design, reasons for corporate crises are broad and diverse. According to Töpfer (1986), the causal complex of corporate crises is visualized in Figure 2.5 and can be further expressed exemplarily as inter alia "intensified competitive pressure, … non-achievement of economies of scale due to declining demand, … insufficient income and cash-flows due to hasty expansions, … [and frequently] no adaptation due to inflexible patriarchs", which is also known as *managerial inertia* (Töpfer, 2013, p. 254).

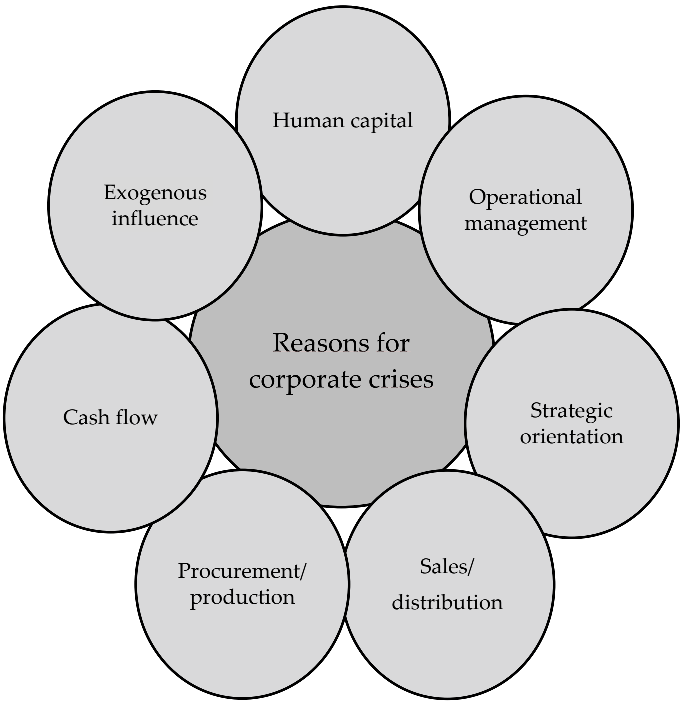

Figure 2.5: Causal complex of corporate crises

[Source: Author's representation based on Töpfer (1986, p. 162)]

2.3.1 Quantitative research on the reasons for corporate crises

A leading source in the evaluation of quantitative data on German corporate insolvencies is the federation of Creditreform, which publishes an annual analysis of insolvencies in Germany (Krystek and Lentz, 2013, p. 35), which will be presented next, supplemented by appraisals by Krystek and Lentz (2013).

The classification by industry is dominated by insolvencies within the service sector. 57.4% (11,130) of insolvencies are attributable to the above-mentioned segment, followed by the trade sector with 20.9% (4,050), 14.3% (2,770) to the construction sector, and 7.5% (1,450) to the manufacturing industry (Creditreform Wirtschaftsforschung, 2019, p. 10). Krystek and Lentz (2013) confirm the current trend and recite annual Creditreform sources in 2012 (Krystek and Lentz, 2013, p. 35).

As far as legal forms are concerned, Figure 1.1 confirms the dominance of insolvencies among sole proprietorships and limited liability companies. Nonetheless, there are slight discrepancies in the reported figures. The latest Creditreform report mentions minor deviations and reassures for 2019 an insolvency rate of 0.6% for listed companies in the German market economy (Creditreform Wirtschaftsforschung, 2019, p. 9). Krystek and Lentz (2013) support this continuity in the long term and underline the significance of the evaluation of insolvencies for listed companies (Krystek and Lentz, 2013, p. 35).

Focusing on company size and revenues, companies with sales figures between EUR 0.5 and EUR 5.0 million show the highest insolvency risk with an insolvency share of 29.1% (5,640) industry (Creditreform Wirtschaftsforschung, 2019, p. 8). Moreover, an increase in insolvency can be observed among larger companies when compared with 2018 data, which ultimately explains the rise in insolvency proceedings for listed companies from 0.5% in 2018 to 0.6% in 2019 (Creditreform Wirtschaftsforschung, 2019, p. 8).

Finally, the age of a company provides further input of characteristics on German insolvencies. Krystek and Lentz (2013) conclude that in 2012, especially young companies between 0 to 4 years after foundation can be associated with a high risk of insolvency, as can mature companies with a history of more than 10 years (Krystek and Lentz, 2013, p. 35). The latest publication by Creditreform in 2019 shows a stable trend in the insolvencies of young companies. In a year-on-year comparison in 2018, the share of companies aged 1 to 2 years has remained stable with a relative share of 8.5%. This is mainly due to improved financing opportunities for start-ups and stable prospects for the establishment of new companies (Creditreform Wirtschaftsforschung, 2019, p. 5). In line with the 2012 results, one can conclude that there is a higher risk for mature companies. Companies with an age of more than 20 years of operation have increased by 15.8% compared to the results of 2015 (Creditreform Wirtschaftsforschung, 2019, p. 5). However, the results presented are often criticized because only insolvent companies are considered, and the data provided offer little information on the reasons for insolvencies and corporate crises, but rather related symptoms and descriptive data for German insolvencies on an annual basis (Krystek and Lentz, 2013, p. 35).

2.3.2 Qualitative research on the reasons for corporate crises

In contrast to quantitative, descriptive research on the reasons for corporate crises, qualitative research follows an inductive approach in the form of expert interviews, structured questionnaires, and other available non-numerical data (Rindfleisch, 2011, pp. 114–115). Major publications of qualitative studies go back to Fleege-Althoff (1930) and have been further developed by inter alia Keiser (1966, Chap. D), Reske, Brandenburg, and Mortsiefer (1976) as well as Hauschild (1983).[6] As Hauschild's multicausal approach is a well-recognized scientific contribution to the literature (Rindfleisch, 2011, p. 120) and allows for a comparison with recent data by means of a follow-up study, it will be outlined exemplary in the following paragraph.

The subject of the analysis is a typology of critical constellations in companies, which goes back to 1983 (Hauschildt, 1983, pp. 142–152). The initial study analyzed 72 mature companies that were mentioned between 1971 and 1982

[6] For a detailed and systematic literature overview of qualitative research on the reasons for corporate crises, see Rindfleisch (2011, p. 116).

in the German journal *Manager Magazin* under the keyword *Mismanagement* (Hauschildt, 1983, pp. 142–152). Using a comparative qualitative content analysis approach, a revised empirical qualitative study examines a sample of 53 cases mentioned in the respective journal in connection with corporate crises between 1992 and 2001. In addition, Hauschildt, Grape, and Schindler (2006) offer a second exploratory approach to the analysis of crisis dynamics and the interrelationships with its causes. The second analysis is based on 19 reorganization plans (Hauschildt, Grape and Schindler, 2006, p. 7), which led to two concluding remarks. First, all the reorganization plans analyzed represent a lack of leadership, and second, the majority of companies are characterized by adjustment crises as operational and/or strategic objectives are not met (Hauschildt, Grape, and Schindler, 2006, pp. 17–18).

Table 2.1: Common causes for corporate crises

This table is based on a comparative qualitative content analysis based on corporate crises. Hauschildt, Grape, and Schindler (2006) analyzed 72 mature companies in the initial study and 53 cases in the follow-up study. Selected companies were classified under the keyword *Mismanagement* in the German journal *Manager Magazin* over a period of more than 10 years prior to the investigation.

Categories for reasons for corporate crises	**Relative frequency (in %)**	
	Initial study (1983)	Follow-up study (2006)
Personnel		
Lack of leadership	15.2	27.5
Inability/inexperience	9.2	5.0
Institutional		
Strategic issues	5.8	9.9
Organizational issues	4.6	6.9
Relation to employees	10.4	5.7
Operative		
Sales/distribution	20.6	12.2

Investments and R&D	8.5	3.9
Production and logistics	11.3	3.9
Other		
Market environment	-	4.1
Market development	-	3.3

[Source: Hauschildt, Grape and Schindler (2006, p. 11ff.)]

However, qualitative empirical research on corporate crises and insolvencies is influenced by the selection bias of individually and subjectively selected observations (Zirener, 2005, p. 25; Rindfleisch, 2011, p. 123), and the methodology does not follow a clear and unambiguous order to generalize the outcome (Rindfleisch, 2011, p. 123; Krystek and Lentz, 2013, p. 37). Therefore, this dissertation applies quantitative approaches to assess the characteristics and determinants of insolvency of non-financial companies listed in CDAX.

2.4 CRISIS MANAGEMENT AND RESULTS

Crisis management is a central concern of management, as organizations are confronted with disruptive events, conflicts, scandals, OBO, or incalculable risks that lead to a corporate crisis or catastrophe (Greve, 2010, p. 46 ff.; Krystek and Lentz, 2013, p. 33; Zamoum and Gorpe, 2018, p. 207). Crisis management can therefore be defined as "an attempt and more or less effective action to cope with the consequences of such occurrences and to initiate and conduct relief operations" (Berthod, Müller-Seitz, and Sydow, 2013, p. 141). Figure 2.6 groups areas of crisis management into reactive and proactive approaches and differentiates further research on an organizational or inter-organizational level. Previous research on crisis management has concentrated mainly on the reactive organizational level of analysis (Lanzara, 1983), and only a few examples of proactive approaches to organizational crisis management have been presented (Weick, Sutcliffe, and Obstfeld, 1999). In the following paragraphs, the above approaches are further elaborated in order to provide a solid theoretical background for crisis management and to point to research work on inter-organizational crisis management.

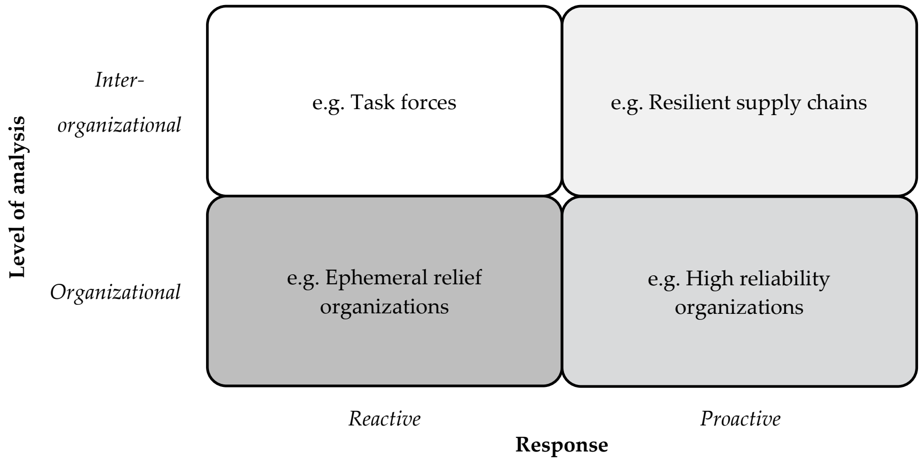

Figure 2.6: Exemplary research areas for crisis management

[Source: Author's representation based on Berthod, Müller-Seitz, and Sydow (2013, p. 141)]

2.4.1 Organizational crisis management

A reactive approach at the organizational level is presented by Lanzara (1983), who analyzes how organizations react to extreme events via spontaneous forms of organization, also known as ephemeral organization. He underlined that after a disaster, such as the analyzed unexpected earthquake in Italy in the 1980s, ephemeral organizations emerged out of emergency entrepreneurship (Lanzara, 1983, p. 73 ff.). The organizations are characterized as ephemeral, fuzzy, and ad-hoc in order to be able to respond reactively (Lanzara, 1983, p. 88). In other words, in times of extreme crises, temporary forms of organization are formed to initiate measures to overcome a crisis. Related literature on reactive organizational crisis management is inter alia provided by Clizbe and Hamilton (2006), who explore the aftermath of organizational crisis management after terroristic attacks (Clizbe and Hamilton, 2006, p. 194), Faraj and Xiao (2006) who address fast-response organizations based on an in-depth investigation of hospitals in unexpected major emergencies (Faraj and Xiao, 2006, p. 1155) or Grube and Storr (2018), who show that entrepreneurs play an essential role in community recovery after disasters following Hurricane Katrina (Grube and Storr, 2018, p. 800).

In contrast, there are various studies that analyze how organizations proactively prepare for corporate crises and unexpected crisis-related phenomena (Weick, 1987; Hutter and Power, 2005; Starbuck, 2009; Mitroff and Storesund, 2020). Weick (1987) analyzes corporate culture in terms of how to deal with unexpected errors. A corporate culture that allows for mistakes and acknowledges their existence may create a positive impact on the management and resolution of corporate crises. He underlines that the socio-psychological factor mentioned above creates a high reliability organization (HRO) (Weick, 1987, p. 112). Weick, Sutcliffe, and Obstfeld (1999) argue that HROs offer organizational effectiveness and are associated with collective mindfulness, as HROs allow "for failure, tendencies to simplify, sensitivity to operations, capabilities for resilience, and temptations to overstructure the system, resulting in an early warning mechanism for crisis" (Weick, Sutcliffe, and Obstfeld, 1999, p. 81). Starbuck (2009) shows that organizations benefit from experiencing rare events such as crises or catastrophes and conclude that "learning from rare events is erratic, but potentially very profitable" (Starbuck, 2009, p. 933). As a final example, Mitroff and Storesund (2020) promote proactive crisis management for socially responsible Tech Companies. Companies in the Tech industry need to be "constantly on the lookout for the unintended consequences of its technologies [and] how they can be abused and misused" (Mitroff and Storesund, 2020, p. 35). However, Berthod, Müller-Seitz, and Sydow (2013) criticize that organizational crisis management mainly "concentrate upon operational issues of recovery and relief, and it does so predominantly in a reactive fashion" (Berthod, Müller-Seitz, and Sydow, 2013, p. 144). Therefore, the inter-organizational approach to crisis management is described below.

2.4.2 Inter-organizational crisis management

A well-known form of crisis prevention is risk management which offers an inter-organizational persepctive (Berthod, Müller-Seitz and Sydow, 2013, p. 144; Oskarsson, Granåsen and Olsén, 2019, p. 517). In this context, the Enterprise Risk Management (ERM) approach enables proactive measures and a cross-organizational perspective (Mehta, 2010, p. 4). While traditional risk management focuses on identifying sources of risk, assessing the potential consequences of crises, and finally on measures to reduce or manage crises and their consequences (Renn, 2008, p. 177 ff.), ERM combines classic internal risk management, supplemented by the analysis of the behavior of competitors and thus of the inter-organizational crisis potential (Mehta, 2010, p. 10). Power (2009) questions the ERM and argues that this approach addresses inter-organizational issues at a superficial level. Annual reports of international companies demonstrate the superficiality of the risk management section, which, according to Berthod, Müller-Seitz, and Sydow (2013), is "usually very short and use a by and- large standardized language shared by all other competitors" (Berthod, Müller-Seitz, and Sydow, 2013, p. 144). In contrast, business continuity management (BCM) can bring about a paradigmatic shift in the way risk management can be reconstructed while taking into account effective inter-organizational crisis management (Power, 2009, p. 849). Initially, BCM evolved during the 1950s, when companies systematically started to store backup copies of critical data electronically (Randeree, Mahal, and Narwani, 2012, p. 473). BCM can be defined as a refined ERM concept taking qualitative factors into account (Berthod, Müller-Seitz, and Sydow, 2013, p. 145). BCM is defined as a

> "holistic management process that identifies potential threats to an organization and the impacts to business operations that those threats, if realized, might cause and which provides a framework for building organizational resilience with the capability for an effective response that safeguards the interests of its key stakeholders, reputation, brand and value-creating activities" (British Standards Institution, 2006, p. 1).

Berthod, Müller-Seitz, and Sydow (2013) argue that BCM lacks the inclusion of inter-organizational measures since this approach attempts to prepare an organization alone to cope with crises and catastrophes with greater resilience. However, network effects are not taken into account (Berthod, Müller-Seitz, and Sydow, 2013, p. 146). The inter-organizational relations (IOR) thus take networks into account. IOR may be viewed as a relationship between two or more legally independent organizations that proactively interact to more effectively overcome inter-organizational crises in contractual forms such as joint ventures, strategic alliances, or noncontractual inter-organizational networks (Berthod, Müller-Seitz, and Sydow, 2013, p. 146). In this context, Järveläinen (2012) proofs that managers use methods such as contracts, audits and standards to improve inter-organizational relationships in the area of outsourcing (Järveläinen, 2012, p. 332). A further distinction can be made here between reactive inter-organizational task forces (Moynihan, 2008) or proactive through the formation of resilient supply chains (Sheffi and Rice, 2005) as shown in Figure 2.6.

2.5 CORPORATE RESTRUCTURING

Since ailing companies face significant problems that lead to corporate crises, a well-organized reactive crisis management can prove its ability by restructuring a company before it is legally obliged to file for insolvency (Klein, 2008, p. 54). In the German literature, the term restructuring is connoted with negative associations among practitioners (Klein, 2008, p. 57). In the literature, however, there is a broad concept, such as the assignment of the term to the scientific area of reorganization research (Finsterer, 1999, pp. 10–11), change management (Iskan and Staudt, 2015, p. 141) and is not limited to corporate crises and threats to the continued existence of an organization (Burtscher, 1996, pp. 60–61).

A widely used term for corporate restructuring in the Anglo-Saxon literature is turnaround management (Buschmann, 2006, p. 25). Turnaround management is related to the prevention of crisis-prone development, and it is defined by Pandit (2000) as the

> "recovery of a firm's economic performance following an existence-threatening decline. The decline may occur over several years although there are situations when extraordinary events occurring over a shorter period of time can place a firm in peril. A successful recovery, in its most subdued form, may involve mere survival with economic performance only just acceptable to the firm's various stakeholders. On the other hand, in its most positive form, the recovery may lead to the firm achieving sustainable, superior competitive positions in its chosen areas of activity" (Pandit, 2000, p. 32).

For the purpose of this dissertation, the term corporate restructuring is used to provide a theoretical basis for the stages prior to insolvency. Restructuring therefore offers a solution to refinance the company and avoid the threat of imminent insolvency. Such out-of-court restructuring measures may include negotiations with stakeholders in case of breaches of contract or the granting of public funds (IDW, 2018a, n. 2). However, corporate restructuring can be carried out not only as out-of-court restructuring but also in accordance with the German Insolvency Statute, which is discussed in more detail in Chapter 3. The following sections provide an overview of the types of restructuring and define the core requirements that are typically addressed in a restructuring report in the streamlined IDW S 6 [7], which was recently published in August 2018.

2.5.1 Forms of corporate restructuring

Corporate restructuring can be categorized into the following types or forms (Hohberger and Damlachi, 2019, p. 95):

(1) *Expansive restructuring*

(2) *Restrictive restructuring*

(3) *Consolidative restructuring*

(4) *Transferring restructuring*

Mergers and acquisitions are based on an expansive restructuring strategy (Piesse et al., 2006, p. 541). The main objective of these measures is to compensate for declining revenues and market share through inorganic growth (Hohberger

[7] IDW Standards (IDW S) set forth the requirements according to which German public auditors provide services other than audit engagements and accounting matters related to business, property and intangible asset valuations, insolvency and restructuring, legally required sale documentation for alternative investment funds, compilation of annual financial statements, and preparation of fairness opinions. In particular, IDW S 6 contains requirements relevant to restructuring reports.

and Damlachi, 2019, p. 101). In this context, economies of scale, tax benefits, fast growth, as well as diversification, can be achieved, enabling even distinct declining entities to overcome corporate crises through successful mergers or acquisitions (DePamphilis, 2014, pp. 5–11). In addition to inorganic growth, an expansive restructuring can also be characterized by organic growth, such as market or product expansion as well as increasing the degree of vertical integration (Hohberger and Damlachi, 2019, p. 102). By contrast, the primary objective of restrictive restructuring is divesture. According to Brauer and Schimmer (2010), the term divesture is described as corporate actions in which a company changes its ownership structure through sell-offs, spin-offs or equity carveouts from a portfolio perspective (Brauer and Schimmer, 2010, p. 84). Corporate divestiture measures ensure liquidity and profitability by adjusting the volume, cost, and capital structure to declining sales figures (Sowell, 2006, p. 107; Hohberger and Damlachi, 2019, p. 96). Frequent accompanying corporate actions in a divestiture phase are the sale of fixed assets, the optimization of the cash conversion cycle, the reduction of full-time employees, the use of credit substitutes such as leasing or factoring as well as the concentration on profit centers and the abandonment of units that generate financial losses (Hohberger and Damlachi, 2019, p. 96). Consolidative restructuring, often referred to as operational restructuring, maintains business operations and improves processes and organizational structure (Hohberger and Damlachi, 2019, p. 99; Zierz and Rieser, 2019, p. 13). In addition to the optimization of business processes and changes in organizational structures, the consolidated restructuring involves changes in product policy, the expansion of services, human resources development, cost reduction programs, refinancing measures, as well as introducing total quality management, and investments in research and development (Hohberger and Damlachi, 2019, p. 99). Finally, the transferring restructuring, also known as asset sale, is defined by a company sale by way of an asset deal (Liebler and Seffer, 2018, p. 644). The company’s viable parts are taken over by a hive-off vehicle, and the remaining old shell is liquidated in line with the judicial system for insolvency proceedings in Germany (Hohberger and Damlachi, 2019, p. 105).

2.5.2 Restructuring expert opinions according to Standard IDW S 6

The aim of a restructuring report by an independent expert is to assess the possibility of restructuring a company in times of crisis. The German Institute of Certified Public Accountants (*Institut der deutschen Wirtschaftsprüfer,* hereinafter referred to as "IDW") defines in its standard S 6, which was updated and streamlined in August 2018, the core requirements that are typically dealt with in a restructuring report (IDW, 2018b). IDW S 6 defines requirements for restructuring opinions and is therefore important because it shows the restructuring capability of companies in the remediation process. Restructuring options are of high importance from a creditor's perspective. Thus, a restructuring opinion and plan are prepared by auditors specialized in the field of corporate crises and insolvencies (IDW, 2018a, n. 6). Apart from the creditor's interest, a restructuring report followed by a restructuring plan offers a strategic reorientation and thus enables the creation of shareholder value. IDW S 6 has been streamlined in its latest edition compared to its predecessor and focuses more on the restructuring requirements for SMEs. The two-stage concept of a restructuring opinion remains unchanged in its latest edition, which is outlined in the following paragraph. The current standard, however, substantiates that an examination of the reasons for insolvency according to IDW S 11 is indispensable (IDW, 2018a, n. 7). Figure 2.7 gives an overview of the core requirements of IDW S 6, which are outlined in the following section.

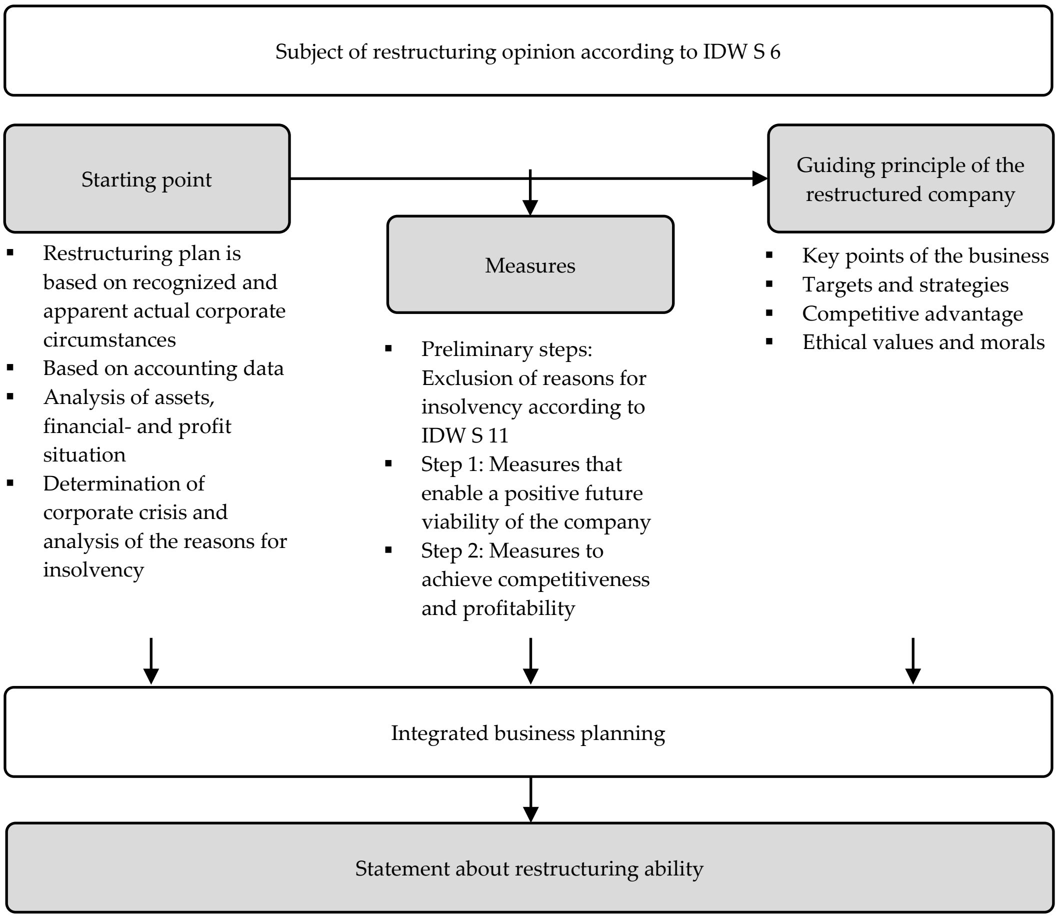

Figure 2.7: Overview of core requirements according to IDW S 6
[Source: Author's representation based on Hermanns (2018, p. 11)]

First and foremost, an assessment of a company's expected ability to continue as a going concern is required (IDW, 2018a, n. 17). In the second instance, an assessment of a company's competitiveness according to IDW S 6 is required (IDW, 2018a, n. 18). Competitiveness is defined as a sustainable business model with capable employees, qualified management, and marketable products or services (IDW, 2018a, n. 25). The updated standard underlines the relevance of the proof of adaptability in a dynamically changing environment. Adaptability is particularly related to the challenges of digitalization (IDW, 2018a, n. 25). If a company fulfills the above-mentioned criteria under the two-stage concept, it is highly likely to overcome a crisis with sufficient profitability and sufficient equity to enable it to be refinanced (IDW, 2018a, n. 26). According to IDW S 6, a sound equity position can be achieved either by reported equity on the balance sheet or, in exceptional situations, by economic equity (IDW, 2018a, n. 29). According to the Ninth Senate of the Federal Court of Justice (*Bundesgerichtshof*, hereinafter referred to as "BGH"), IDW S 6 has decided to meet the criteria of an appropriate profitability ratio (BGH, 12.05.2016 – IX ZR 65/14). In addition, IDW S 6 states that, compared with the lower range of industry-specific average values, a sufficient equity base and adequate profitability is achieved. In the absence of a relevant market, the following alternatives are proposed. In order to formulate a positive restructuring opinion, rating-based methods should propose an *investment grade* rating or use financial ratios such as net debt divided by budgeted EBITDA (IDW, 2018a, n. 28). In summary, it can be said that it is important to derive an adequate basis for refinancing through the methods applied.

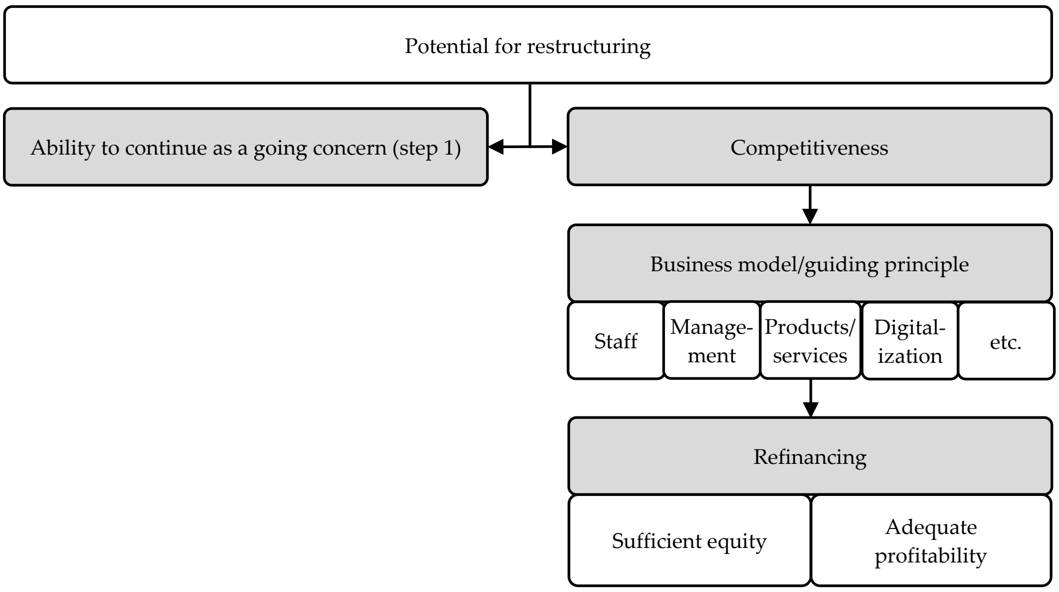

Figure 2.8: Potential for restructuring according to IDW S 6
[Source: Author's representation based on IDW (2018a, n. 24)]

Once the restructuring potential has been confirmed, the severity of the corporate crisis must be identified in order to formulate effective measures. According to IDW S 6, six crisis stages are distinguished (IDW, 2018a, n. 62):

(1) Stakeholder crises

(2) Strategic crises

(3) Product- and sales-related crises

(4) Profitability crises

(5) Liquidity crises

(6) Insolvency

The crisis stages presented show similarities with the four-phase model of Müller (1982), supplemented by stakeholder crises as well as product and sales-related crises. As explained in Section 2.2.2, the scope for action depends on the severity of the crisis, and accordingly, measures are aligned by restructuring concepts. In the event of a liquidity crisis, short-term measures to maintain business operations are initiated before the reasons for the corporate crisis are addressed (IDW, 2018a, n. 33).

As a starting point, actual and relevant company data are needed to formulate a restructuring plan. According to IDW S 6, relevant data includes organizational, legal, and tax information as well as performance, financial, and personnel-related facts (IDW, 2018a, n. 54). In this context, all relevant data sources shall be presented clearly and concisely by naming all information sources (IDW, 2018a, n. 53). In addition to an internal analysis of the company's strengths and weaknesses, external factors with a focus on opportunities and risks are also taken into account when applying quantitative and qualitative measures (IDW, 2018a, n. 56). With regard to internal strengths and weaknesses, the quality of the potentials of the management, personnel, procurement, production, sales, technology, innovation, as well as the financial potential, is evaluated in order to derive effective measures for the above-mentioned workstreams (IDW, 2018a, n. 57). This process is coordinated with top management on the basis of expertise and the ability to implement effective measures (IDW, 2018a, n. 56). Subsequently, relevant external factors such as technology advances, economic trends, political, environmental, and economic regulations are identified in order to formulate an effective action plan (IDW, 2018a, n. 58) with estimated financial implications for the company for the next budgeted year, cascaded at monthly intervals, followed by a quarterly overview or half-yearly estimates for the medium-term planning (IDW, 2018a, n. 74). Formulated actions may include not only internal responsible persons, but also third parties, such as an agreement to suspend interest payments, sell assets, increase capital from company funds, or waive Christmas bonuses at the request of employee representatives (IDW, 2018a, n. 76). Finally, all workstream-related measures are to be brought together in an integrated restructuring plan in order to enable synergies to be achieved and the overall effects to be monitored (IDW, 2018a, n. 77). On the basis of the integrated restructuring plan, a planned profit and loss account and a balance sheet are compulsory as part of the financial planning, which is cascaded at monthly intervals for the budgeted period, followed by quarterly or half-year results for the subsequent periods (IDW, 2018a, n. 78). As target figures are strongly influenced by the underlying action plan, a sensitivity analysis is proposed to take into account different outcomes of refinancing (IDW, 2018a, n. 80). In a nutshell, the requirements for restructuring concepts according to IDW S 6 have been streamlined and illustrate a legally secure process for the development of a restructuring concept not only in Germany but also at the EU level (BDO AG Wirtschaftsprüfungsgesellschaft, 2019).

2.6 CONCLUSION

Corporate crises endanger the achievement of dominant corporate goals, which first leads to value destruction and threatens the survival of a company (Krystek, 1987, pp. 6–7; Drukarczyk and Schöntag, 2020, p. 43). Corporate crises are unplanned and unintended events with ambivalent outcomes (Krystek, 1987, p. 6). Furthermore, complex decision-making is required since the demands on crisis management increase with the severity of crises, while at the same time the scope for countermeasures decreases (Röthig, 1976, pp. 13–15). The reasons for corporate crises can be explained by crisis symptoms, which can be distinguished between internal and exogenous crisis symptoms. Krystek and Lentz (2013) criticize, against the background of quantitative research on corporate crisis grounds, that underlying data provide little information on the reasons for insolvencies and corporate crises, but rather the symptoms and descriptive data for German insolvencies on an annual basis (Krystek and Lentz, 2013, p. 35). As a leading source in the evaluation of annual quantitative data on German corporate insolvencies, the publications of Creditreform are presented. First and foremost, the chosen descriptive approach does not follow a clear and unambiguous order to generalize the outcomes (Krystek and Lentz, 2013, p. 37). Furthermore, qualitative empirical research on corporate crises and insolvencies is influenced by the selection bias of individually and subjectively selected observations (Zirener, 2005, p. 25; Rindfleisch, 2011, p. 123). As a key finding derived from Chapter 2.3.2, qualitative research follows an inductive and exploratory approach based on non-numeric data and is limited in assessing and quantifying determinants of corporate default (Hauschildt, Grape and Schindler, 2006; Krystek and Lentz, 2013, p. 37; Behringer, 2017, pp. 23–26; Rindfleisch, 2011, pp. 114–115). Therefore, this dissertation applies quantitative statistical approaches to assess the characteristics and determinants of insolvency for non-financial companies listed in the CDAX and evaluates and extends global PD models. This course of action is consistent with numerous academic research in recent decades (Altman, 1968; Ohlson, 1980; Shumway, 2001; Campbell, Hilscher, and Szilagyi, 2008; Mertens, Poddig, and Fieberg, 2018) and lays the cornerstone for the empirical part in Chapter 5. In advance, a systematic literature review on PD models is detailed in Chapter 4.1 to lay theoretical foundation for the research objectives in this dissertation.

Once organizations enter a state of a corporate crisis, crisis management is a central tool to counter the consequences of corporate crises; therefore, countermeasures are developed and implemented (Berthod, Müller-Seitz, and Sydow, 2013, p. 141). The latest research findings on crisis management, divided into organizational (Lanzara, 1983; Weick, 1987; Clizbe and Hamilton, 2006; Mitroff and Storesund, 2020) and inter-organizational crisis management (Sheffi and Rice, 2005; Moynihan, 2008; Järveläinen, 2012; Oskarsson, Granåsen and

Olsén, 2019), is presented to allow a better understanding of proactive and reactive approaches and their possible outcomes. Finally, the forms of corporate restructuring as part of successful crisis management are discussed in the light of the recent changes in restructuring concepts, namely the streamlined IDW S 6. In the event of an unfruitful turnaround, filing for insolvency is the subsequent legally binding procedure, which is important for the purposes of this dissertation in order to obtain an indicator of the insolvency of German non-financial companies listed in the CDAX.

3 CORPORATE INSOLVENCY

Terminology relating to the financial distress of companies is diverse and sometimes used interchangeably. Four generic terms frequently encountered in the literature are: *failure, insolvency, default*, and *bankruptcy* (Altman and Hotchkiss, 2006, p. 4). The aim of this chapter is to delimit the above-mentioned terms, to present the key stakeholders in insolvency proceedings concerned, and define the standard process for insolvency proceedings in Germany. In a synthesis of the theoretical background to theories dealing with corporate crises, which are presented in Chapter 2, financial distress can be assigned to the later phases of Krystek (1987) and Müller (1982). Financial distress, in particular, characterizes the transformation of the state from financial health to a financial crisis. However, a clear operationalization of this change of state is widely discussed in scientific contributions (Altman, 1968; Ohlson, 1980; Shumway, 2001; Campbell, Hilscher, and Szilagyi, 2008). For instance, Campbell, Hilscher, and Szilagyi (2008) propose a two-fold approach. First, Campbell, Hilscher, and Szilagyi (2008) comment on an explicit definition of financial distress and refer this term to certain events such as insolvency proceedings. In contrast, they also define financial distress in a broader sense and consider a situation where financial conditions deteriorate over time to such an extent that the risk of an event such as insolvency or liquidation may be a realistic outcome (Campbell, Hilscher, and Szilagyi, 2008, p. 2900).

The development of a PD model for German-listed companies requires a clear definition of corporate failure to ensure the robustness and consistency of the empirical findings. A study by Bahnson and Bartley (1992) confirms that the results of PD models can be influenced by the definition of failure used and emphasizes that future studies should pay particular attention to a clear definition. In accepted academic PD research, "the collection of data for bankrupt firms requires a definition of failure and delimitation of the population to ensure robust findings" (Ohlson, 1980, p. 114). For instance, the sample in Altman's original study (1968) included, "manufacturers that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act" (Altman, 1968, p. 593). Ohlson (1980) followed the same legal definition and selected companies that must "file for bankruptcy in the sense of Chapter X, Chapter XI, or some other notification indicating bankruptcy proceedings" (Ohlson, 1980, p. 114). Therefore, all terminologies related to default, such as *bankruptcy*, *failure,* and *insolvency* could be bundled and concisely distinguished from a legal perspective.

In light of leading academic literature, as highlighted in Appendices A-4.1 to A-4.3, this dissertation defines default according to the legal concept of insolvency under the national statute InsO. The next chapter therefore deals in detail with the reasons for insolvency proceedings in Germany, the standardized process for opening proceedings, the main parties involved as well as legislative changes during the period of the empirical study.

3.1 GROUNDS FOR INSOLVENCY PROCEEDINGS IN GERMANY

Insolvency is a state of financial distress in which an individual or organization is unable to meet its obligations when due (CFI Education Inc., 2019). However, the root of the problem lies in the generic definition of the term. The applicable laws differ from country to country and therefore offer different definitions of insolvency, resulting in completely different meanings (Eales, 1996, pp. 12–15). The German Insolvency Statute (*Insolvenzordnung*, hereinafter referred to as "InsO") primarily serves the satisfaction of the creditors of insolvencies. An essential role in achieving this goal is played by the appointment of the insolvency administrator, who administers all pending creditors' claims in the proceeding (Nickert, 2016). After deducting the expenses of the legal proceedings and the obligations from the remaining assets, the insolvency administrator distributes outstanding claims in an order detailed in the insolvency plan (Nickert, 2016). Hence, the primary objective of all German insolvency proceedings is, therefore, the best possible satisfaction of creditors' claims (Heesen and Wieser-Linhart, 2018, p. 19).

The German Insolvency Statute forms the legal basis for insolvency proceedings and its definition. The opening requires a reason for insolvency (*Insolvenzordnung (InsO)*, 2020, Sec. 16). The Insolvency Statute defines three insolvency grounds, which form the basis for a substantial definition of terminology from a legal perspective. The first two out of three insolvency reasons below lead to a mandatory insolvency petition, while the latter allows voluntary insolvency proceedings (*Insolvenzordnung (InsO)*, 2020, Sec. 16):

(1) *Inability to pay due obligations*
(2) *Overindebtedness*
(3) *Impending insolvency*

In light of the presented insolvency reasons, it is important to mention that the presented grounds for insolvency have been subject to punctual changes as temporary legal amendments and suspensions have been embedded in InsO throughout recent years. On October 18, 2008, a temporary reformulation of the term overindebtedness based on Article 5 of the German Financial Market Stabilization Act (*Finanzmarktstabilisierungsgesetz*, hereinafter referred to as "FMStG") has been introduced to facilitate symptoms of the global financial crisis in 2008 (Schunder, 2008, p. 695; Gundlach, 2020, n. 23). The legal definition before October 2008 of overindebtedness did not consider the assessment of a positive going-concern forecast. The amendment in judicial proceedings of overindebtedness introduced a two-track definition, i.e. arithmetical insolvency and a subsequent forecast of continuation as presented in Chapter 3.1.2. Initially, this softening of the legal term overindebtedness was restricted to a transitional period of application from October 18, 2008 until December 31, 2013. However, this transitional arrangement was later embedded in the current German Insolvency Statute (Gundlach, 2020, n. 23).

In response to the COVID-19 pandemic and its far-reaching economic impact, on March 27, 2020, major suspensions to InsO have been introduced by the German COVID-19 Insolvency Suspension Act (*COVID-19-Insolvenzaussetzungsgesetz*, hereinafter referred to as "COVInsAG"). According to COVInsAG, the obligation to file for insolvency proceedings due to overindebtedness and the inability to pay due obligations has been initially suspended until September 30, 2020 if a company is subject to the following conditions (*COVID-19-Insolvenzaussetzungsgesetz (COVInsAG)*, 2020, Sec. 1(1)):

(1) A company's insolvency is a consequence of the COVID-19 pandemic and
(2) there are prospects of successfully resolving the inability to pay due obligations.

In light of the aforementioned criteria, the insolvency is presumed to be the result of the COVID-19 pandemic in case the debtor was able to pay its due obligations on December 31, 2019 (Hörtnagl and Bode, 2020, p. 458). Based on the dynamics in the COVID-19 pandemic, the necessity to file for insolvency due to overindebtedness has been prolonged to December 31, 2020 (Hörtnagl and Bode, 2020, p. 458). Under the current law, the discussed suspension measures may be prolonged until April 30, 2021 (BMJV, 2021).

Figure 3.1 summarizes the process of the reasons for opening insolvency proceedings highlighted above. Obligation and the right to apply for insolvency proceedings must be distinguished from a debtor's perspective in order to avoid personal criminal and financial liabilities (Wilhelm et al., 2017, p. 2). Furthermore, the objective of mandatory justification of the application is to protect the claims of creditors from a further reduction in the insolvency assets and to promote transparency for new creditors before concluding contracts with distressed companies (RegE MoMiG, 2007, p. 55).

If there are compelling reasons for the inability to pay obligations when due, both legal entities and natural persons are obliged to file for insolvency (*Insolvenzordnung (InsO)*, 2020, Sec. 15). Second, legal entities and equivalent commercial partnerships are required by law to file for insolvency proceedings if overindebtedness is established (*Insolvenzordnung (InsO)*, 2020, Sec. 19). Finally, the impending insolvency is a voluntary reason for insolvency. Therefore, both parties have the right to apply for an opening proceeding (*Insolvenzordnung (InsO)*, 2020, Sec. 18). In addition, creditors can also apply for the opening of insolvency proceedings in Germany (Wilhelm et al., 2017, p. 2; *Insolvenzordnung (InsO)*, 2020, Sec. 15).

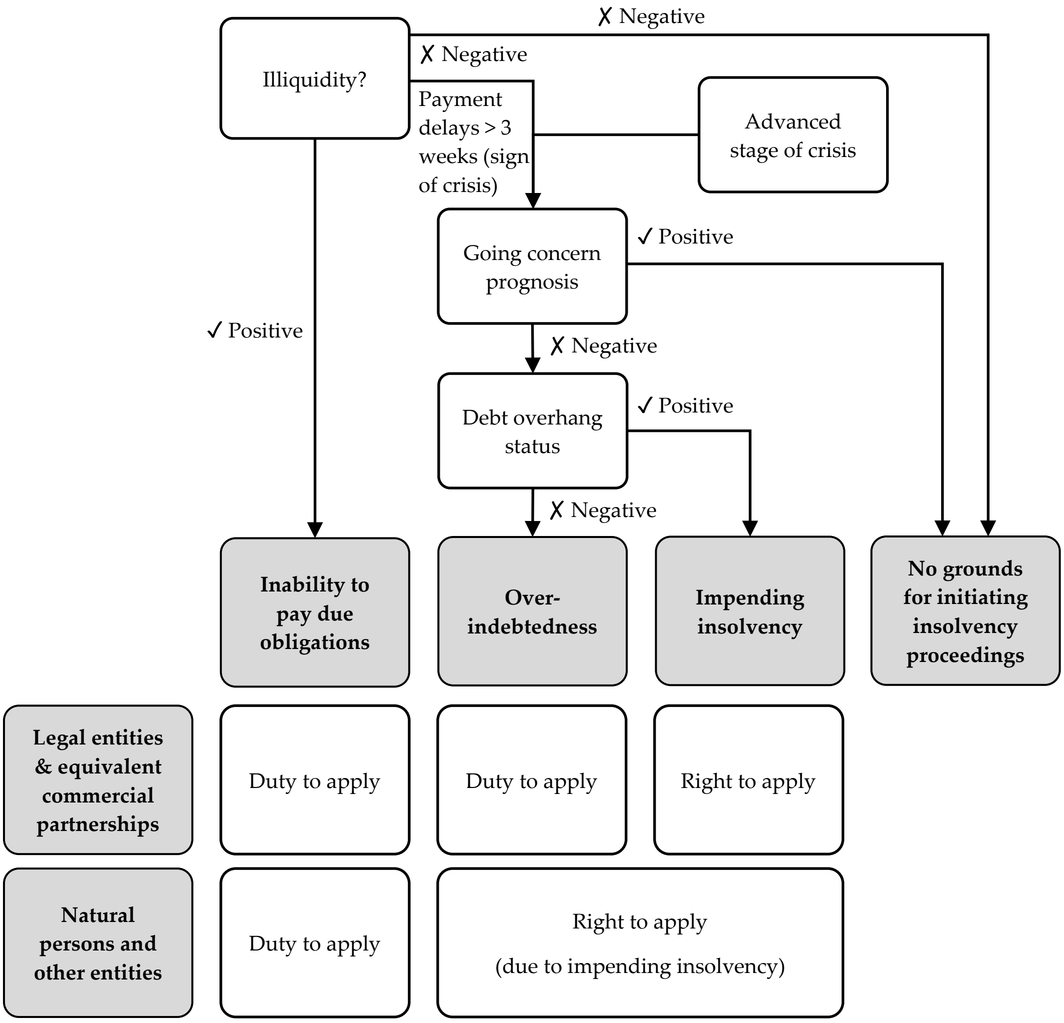

Figure 3.1: Flowchart of reasons for insolvency proceedings
[Source: Author's representation based on Martin and Bieckmann (2014, p. 2)]

3.1.1 Inability to pay due obligations

Insolvency is primarily defined as the inability to pay one's obligations when due. Therefore, a debtor is considered insolvent if he is not able to meet his due obligations (*Insolvenzordnung (InsO)*, 2020, Sec. 17). Heesen and Wieser-Linhart (2018) argue that the definition presented was deliberately broadly defined in order to leave enough leeway for further legal developments. Therefore, legal terms are generally vague and must be derived from current case practice (Heesen and Wieser-Linhart, 2018, p. 5). In the light of current case practice, a distinction must be made between temporary stagnation of payments and a general inability to settle commitments when due (Lehmann, 2018). By entering into loan agreements and active receivables management, a temporary payment holdup can be resolved and thus does not require insolvency proceedings (Heesen and Wieser-Linhart, 2018, p. 5).

In this context, the BGH has operationalized an appropriate time frame and threshold values to quantify the inability to pay the obligations due (BGH, 24.05.2005 – IX ZR 123/04). Liquidity gaps that are not substantial and only temporary do not constitute a reason for mandatory insolvency proceedings and are defined only as a late payment (Lehmann, 2018). Temporary financing gaps of up to 10% within a three-week time frame are generally tolerated (BGH, 24.05.2005 – IX ZR 123/04). In the event that a financing gap cannot be closed within the aforementioned three weeks, an alternative approach to assessing illiquidity must be applied, which is not mentioned in the guidelines of the BGH ruling (Zabel and Pütz, 2015, p. 916).

Therefore, the German Institute of Certified Public Accountants (*Institut der deutschen Wirtschaftsprüfer*, hereinafter referred to as "IDW") introduced additional conditions for the assessment of temporary financing gaps in its standard IDW S 11. Refinancing gaps of less than or equal to 10% that are not expected to be filled within 3 months, in special cases up to 6 months, are unacceptable and defined as liquidity gaps (IDW, 2015, n. 17).

In a nutshell, a debtor must be able to pay at least 90% of his or her due liabilities within three weeks to avoid insolvency proceedings (Graf, 2018, p. 176). If the debtor exceeds the tolerances shown, the judicial insolvency proceedings become binding (Lehmann, 2018). Accordingly, the illiquidity test introduced in 2005 is the sum of the available liquidity (*Liquidity 1*) and the forecast liquidity within the next three weeks (*Liquidity 2*) in relation to the total liabilities due and requested for payment at the respective time (*Liabilities 1*) (Lehmann, 2018). However, the recognition of new liabilities that arise during the three-week assessment period is not taken into account in the present calculation (Graf, 2018, p. 175). Restructuring specialists and practitioners called this derecognition as *bow wave theory* (*Bugwellentheorie*) (Lehmann, 2018). Like the bow of a ship on rough seas, it allowed companies to advance maturing liabilities in significant amounts (Graf, 2018, p. 175). The aforementioned "requirement being that working capital generated within the next three weeks would be sufficient to reduce those liabilities to below 10%" (Lehmann, 2018). Since the proposed loophole in the law has been criticized, the BGH, in his most recent case law goes into more detail on the aspect of assessing the solvency of a debtor and rejects the *bow wave theory* on the illiquidity test (BGH, 19.12.2017 - II ZR 88/16). Illiquidity is then calculated by determining the ratio between the sum of Liquidity 1 and Liquidity 2 and comparing it with the sum of Liability 1 and Liability 2, which represents liabilities that arose during the three-week assessment period (BGH, 19.12.2017 - II ZR 88/16).

3.1.2 Overindebtedness

The second reason for insolvency is defined by overindebtedness, which exists when the debtor's assets no longer cover his existing payment obligations unless it is very likely that the company will continue to exist (*Insolvenzordnung (InsO)*, 2020, Sec. 19). Furthermore, overindebtedness is only a reason for insolvency for legal entities (*Insolvenzordnung (InsO)*, 2020, Sec. 19). Although this presented reason for insolvency in Germany requires statutory legal proceedings, the clear definition is sometimes unknown among practitioners (Heesen and Wieser-Linhart, 2018, p. 9). In short, judicial proceedings of overindebtedness can be identified by a two-track definition, i.e. arithmetical insolvency and a subsequent forecast of continuation (Gundlach, 2020, n. 27).

In the event of arithmetical insolvency, all assets are compared with the liquidation values. In case of a debt overhang, arithmetical insolvency may be declared, which is the first requirement for legally binding insolvency proceedings in Germany. One tool for deriving an overindebtedness status is the so-called *excessive indebtedness balance sheet*, which primarily has an objective and informative function (Schwab and Schulz, 2007, pp. 60–62). The following scheme shown in Table 3.1 can be used as a template to illustrate a realistic situation of all assets and liabilities:

Table 3.1: Schematic representation of an excessive indebtedness balance sheet

This table provides an overview of an excessive indebtedness balance sheet for the assessment of arithmetical insolvency as part of a two-tier definition, i.e. arithmetical insolvency and a subsequent continuation prognosis to determine the overindebtedness according to InsO Sec. 19.

Assets:	
Tangible fixed assets	Tangible and fixed assets can be calculated as the assumed net proceeds from immediate sales (proceeds – costs of disposal)
Intangible assets	Intangible assets may only be recognized if they can be used independently. Any goodwill arising must be recognized when the company is available for sale.
Inventories	Inventories are recognized and measured at the current market price (if available). Recognized values, however, are dependent on industry and business trends and thus depend on the personal judgment of the respective insolvency administrator. The raw material is generally valued with a residual value of 0 if no short-term liquidation can be realized in a suitable marketplace. Semi-finished goods are often recognized at residual value or even 0, as the last finishing step is still outstanding. Finished goods are generally valued at 40-60% of book value.
Receivables	Recognition according to the recoverability and dunning level of the receivables.
Accrued income	Accrued income, e.g., rent paid in advance will only be recognized if claims for reimbursement arise due to premature termination.

Liabilities:	
Contributions from silent partners	Contributions by silent partners are only to be taken into account if either the capital contribution of a silent partnership exceeds the losses incurred or the silent partner is not liable for losses incurred.
Provisions	Provisions for severance payments and pensions are recorded at present value. Deferred income tax is provided on the realization of hidden reserves to allow for the tax consequences.
Liabilities	Liabilities include overdue liabilities, but also current, non-current as well as contingent liabilities.

[Source: Author’s representation based on Heesen and Wieser-Linhart (2018, pp. 11–12)]

Subsequently, the probability prognosis of a possible insolvency is assessed in a continuation forecast (Zabel and Pütz, 2015, p. 918). A positive going-concern forecast is defined as a sustainable turnaround that includes both a reduction in annual losses and a subsequent return to positive operating results (von Berkstein, 2010, p. 24). This analysis, carried out by experts, includes potential and actual causes of losses, preparation of a finance plan as well as estimates of the future prospects of a going-concern assumption (Heesen and Wieser-Linhart, 2018, p. 10). The German Commercial Code (*Handelsgesetzbuch*, hereinafter referred to as “HGB”) regulates the going-concern principle in Sec. 252 (1). The valuation must be based on the continuation of the company's operations, unless there is a factual or legal assumption to the contrary (HGB, 2020, Sec. 252 (1)). To operationalize such an analysis, Heesen and Wieser-Linhart (2018) propose the following measures and their operationalization, which are presented in Table 3.2.

Table 3.2: Measures of a positive going-concern forecast

This table presents an overview of the measures for assessing a positive going-concern forecast as part of a two-tier definition, i.e. arithmetical insolvency and a subsequent going-concern forecast to determine overindebtedness according to InsO Sec. 19.

Measures	**Operationalization**
Financing measures by shareholders or external third parties	Legally binding commitment mandatory
Borrowing	Creditworthiness generally sufficient
Waiver of creditors' claims	Legally binding commitment mandatory
Out-of-court settlement	High probability (>50%) acceptance rate
Negotiations on the sale of companies	No legally binding commitment is mandatory. However, an objective forecast of probable company sales is necessary.

[Source: Author's representation based on Heesen and Wieser-Linhart (2018, p. 13)]

As highlighted in Table 3.2 above, a positive going-concern forecast depends on a number of factors. According to IDW S 11, a 24-month rolling forecast period is prepared in which the future viability of the company is clearly visible (IDW, 2015, n. 60). In other words, a company that is currently in an arithmetical insolvency situation is not insolvent as long as a positive going-concern forecast for the next 24 months is feasible (IDW, 2015, n. 60; Gundlach, 2020, n. 27). In summary, it can be said that a negative outcome of both the arithmetical and the going-concern forecast forms the legal basis for compulsory insolvency proceedings in Germany (Gundlach, 2020, n. 27).

In this context, Heesen and Wieser-Linhart (2018) give a vivid example to support the combination of arithmetical insolvency with a consecutive going-concern forecast. The valuation of ongoing projects in capital-intensive industries with liquidation value will lead to a substantial debt overhang due to the high capital expenditures. The consideration of these long-term projects and the associated value added does not constitute a reason for insolvency proceedings. One after the other, a positive business outlook must be determined in order to overcome overindebtedness under the German Insolvency Statute (Heesen and Wieser-Linhart, 2018, p. 10).

3.1.3 Impending insolvency

In order to increase the chances of restructuring and reorganization of companies, legislators introduced impending insolvency, which is also known as a reason for imminent insolvency (Wendler, Tremml, and Buecker, 2008; *Insolvenzordnung (InsO)*, 2020, Sec. 18). At this stage, it is unlikely that the debtor will be able to meet his due obligations but he usually has more assets, which increases the insolvency assets (Gundlach, 2020, n. 18). As explained in Section 3.1, impending insolvency is not a compelling reason for filing for insolvency proceedings in Germany. However, the voluntary opening of insolvency proceedings is the basis for the restructuring and reorganization of companies and for avoiding payment defaults (Gundlach, 2020, n. 17). The terminology of impending insolvency is not legally defined any further.

3.2 ESUG: MODERNIZATION OF CORPORATE RESTRUCTURING IN GERMANY

In recent decades, German insolvency law has been one of the consistently and severely criticized areas of German federal legislation (Höher, 2012, p. 16). A legal reform to amend the national bankruptcy law, which was codified in the Bankruptcy Act of 1877, was therefore a major concern. According to the Introductory Act to the Insolvency Statute (*Einführungsgesetz zur Insolvenzordnung*, hereinafter referred to as "EGInsO"), the new Insolvency Statute (InsO) came into force on 01 January 1999 (*Einführungsgesetz zur Insolvenzordnung (EGInsO)*, 1994, Sec. 110) and replaced the Bankruptcy Act of 1877, the Settlement Act in the West German States, and the Total Execution Act in the former East German States

(Remmert, 2007, p. 1). In recent years, the Insolvency Statute has been further improved. Recent legislative changes are presented in the following section as punctual amendments and the introduction of new measures may play a crucial role in the empirical assessment and enhancement of default risk for German non-financial entities.

In March 2012, German lawmakers fundamentally reformed essential parts of the country's insolvency law by implementing the law to further facilitate the restructuring of companies (*Gesetz zur weiteren Erleichterung der Sanierung von Unternehmen*, hereinafter referred to as "ESUG") (Moldenhauer and Wolf, 2017, p. 2).

> "The key aim of the legislative change lays in strengthening creditors' rights through earlier involvement and greater influence in the selection of the insolvency administrator. From a debtors' perspective, the ESUG creates incentives to apply for the opening of insolvency proceedings at an early stage in order to enhance the chances of successfully restructuring the company. Hence, self-administration has been strengthened, protective shield proceedings introduced and the insolvency plan procedure streamlined" (Ledwon and Jäger, 2020, pp. 75–76).

Taking into account the legislative changes presented, the updated Insolvency Statute offers strategic options and moves in the direction of a restructuring culture which, thanks to an extended creditor autonomy and transparency initiatives compared to the previous legislation, enables the early opening of insolvency proceedings (Backert et al., 2009, p. 274). Figure 3.2 summarizes the ESUG and recent legislative changes on a time axis:

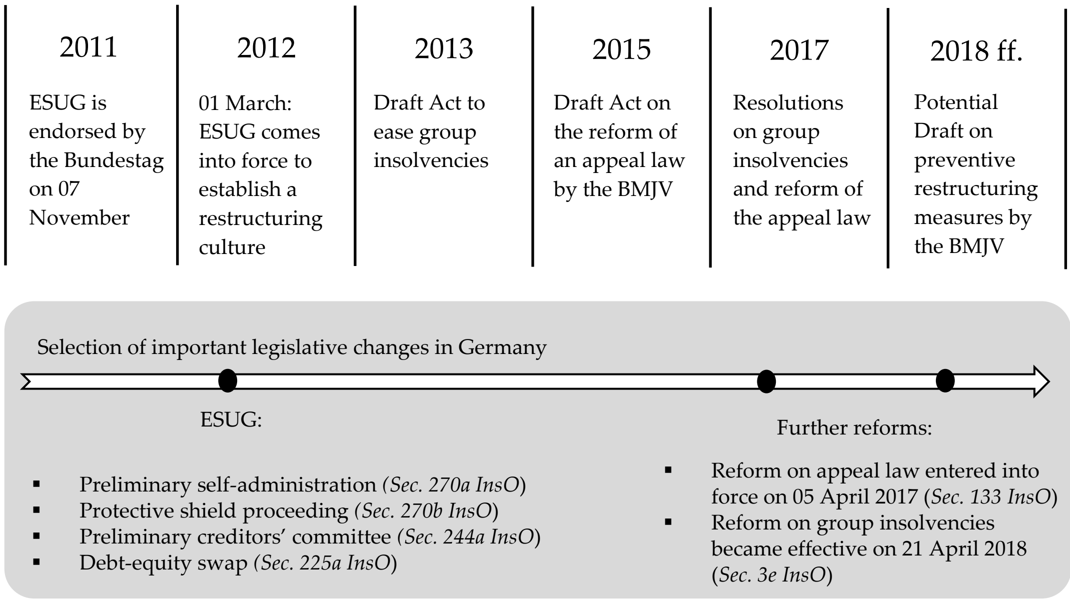

Figure 3.2: Timeline ESUG and relevant legislative amendments
[Source: Author's representation based on Eschmann, Blatz, and Seagon (2018, p. 10)]

3.2.1 Strengthening creditors' rights

The first pillar of the ESUG reform focuses on improving creditors' rights in insolvency proceedings (Wilhelm et al., 2017, p. 2). The ESUG creates the legal basis for debtors and creditors to propose an insolvency administrator (Moraht and Lütcke, 2012). According to Höher (2012), the proposed person may have previously participated in the course of insolvency proceedings without losing the necessary independence (Höher, 2012, p. 18). Prior to the introduction of ESUG, the provisional insolvency administrator could have the possibility to seek the early liquidation of a debtor's assets within the first three months in order to reduce personal liability while receiving the full benefit in the form of salary payments (Meyer-Löwy, Pickerill, and Plank, 2012, p. 2). The main objective is to involve creditors in proceedings at an early stage in order to avoid being confronted with unsatisfactory outcomes of proceedings (Moraht and Lütcke, 2012). Therefore, the second legislative change introduced a provisional creditors' committee (Meyer-Löwy, Pickerill, and Plank, 2012, p. 1). In particular, the committee can counteract the potential value-destroying decisions of insolvency administrators and thus promote transparency and predictability (*Insolvenzordnung (InsO)*, 2020, Sec. 225a). The provisional creditors' committee can be nominated during the application procedure (Moraht and Lütcke, 2012). The explicit requirements for voluntary and mandatory appeals are regulated as follows. The competent insolvency court may appoint a provisional creditors' committee at its discretion during the application procedure (Moraht and Lütcke, 2012). If such a request is made by either the debtor, the provisional administrator, or any creditor, the competent court should establish such a committee (Moraht and Lütcke, 2012). In particular, insolvency courts are obliged to appoint a provisional creditors' committee if the debtor meets at least two of the following three criteria (*Insolvenzordnung (InsO)*, 2020, Sec. 22 a):

(1) *A balance sheet total of at least EUR 6.0 million after deduction of negative equity in accordance with Section 268 (3) HGB.*
(2) *Revenue of at least EUR 12.0 million within the previous financial year.*
(3) *An annual average of at least 50 employees.*

Finally, the Federal Ministry of Justice and Consumer Protection (*Bundesministerium der Justiz und für Verbraucherschutz*, hereinafter referred to as "BMJV") evaluated the ESUG amendments in 2018 and welcomed the improvement of creditors' rights (Jacoby et al., 2018, pp. 19–20).

3.2.2 Strengthening self-administration

The strengthening of self-administration rights is closely related to the strengthening of creditors' rights. In case the provisional creditors' committee backs the debtor's petition for self-administration without exception, the court in charge must not reject such an application (Nerlich, 2019, n. 193). Prior to the entry of the ESUG in 2012, the filing for insolvency generally led to the assignment of a provisional insolvency administrator (Wilhelm, Richter, and Lach, 2012, p. 3). The managing directors of the insolvent company were therefore only allowed to act with the approval of the provisional insolvency administrator (Wilhelm, Richter, and Lach, 2012, p. 3). The possibility for the debtor to steer the insolvency proceeding by self-administration was also only exceptionally permitted by the courts (Wilhelm, Richter, and Lach, 2012, p. 3).

In accordance with the ESUG, the self-administration process has improved. Although a change in legislation simplified self-administration, the latest ESUG review by the Boston Consulting Group (BCG) shows that the current share of self-administration proceedings remains unchanged since 2012 at the level of 2.6% of all insolvency proceedings (Moldenhauer and Wolf, 2017, p. 15). However, self-administration has recently gained interest in the largest insolvency cases in Germany. The BCG report concluded that more than 58% of the largest 50 corporate insolvencies in 2016 were handled as self-administered proceedings, a sharp increase from 30% in 2012 (Moldenhauer and Wolf, 2017, p. 15).

3.2.3 Introducing protective shield proceedings

With the ESUG, a new protection concept was introduced into the German Insolvency Statute in 2012. The purpose of a protective shield proceeding is to encourage earlier filings to open insolvency proceedings (Seagon, 2014, n. 2). For a period of three months, debtors can concentrate on reorganization measures and draw up a restructuring plan in self-administration under the supervision of a provisional insolvency trustee, while benefiting from all enforcement measures (Höher, 2012; Bitzer, 2020, n. 195e). The protective shield method is presented in Section 3.3.3 as it is regulated under the current legal framework in Germany.

3.2.4 Introducing debt-equity swaps as a restructuring instrument

Following the introduction of ESUG in 2012, German insolvency law allows debt-equity swaps as a restructuring instrument as part of an insolvency plan. In a restructuring, a debt-equity swap converts the debts of outstanding creditors into shares or membership rights within the debtor's company through a non-cash capital increase or share deal (Braun, 2020, nn. 4–8). The main objective of this restructuring instrument is therefore to reduce overindebtedness and optimize a debtor's liquidity in terms of an improved equity share (Heesen and Wieser-Linhart, 2018, p. 88; Braun, 2020, n. 9). The use of a debt-equity swap requires the consent of all debtors whose debts are to be converted (Höher, 2012, pp. 18–19). The most recent study by Roland Berger in cooperation with HgGUR (*Heidelberger gemeinnützige Gesellschaft für Unternehmensrestrukturierung*, hereinafter "HgGUR") concludes that in practice there is an immense lack of knowledge and experience in the implementation of concrete financial restructuring instruments (Eschmann, Blatz, and Seagon, 2018). For instance, two-thirds of all participants have not used a debt-equity swap or do not intend to place a debt-equity swap in the future (Eschmann, Blatz, and Seagon, 2018, p. 6).

3.2.5 Streamlining insolvency plan proceedings

Another aim of the ESUG reform is to improve and streamline insolvency plan procedures. Even before the ESUG came into force, the German Insolvency Statute was offered insolvency proceedings subject to creditor approval (Wilhelm, Richter, and Lach, 2012, p. 4). However, the implementation of an insolvency plan was negatively affected by the encroaching rights of the shareholders of the insolvent company, which led to a considerable delay. After the inception of the ESUG, Sec. 225a of the InsO allows to override the aforementioned shareholder rights of the insolvent company and thus strengthens the majority rights regulated in Section 244 (Moraht and Lütcke, 2012; *Insolvenzordnung (InsO)*, 2020). Finally, the competent court may prohibit enforcement measures by creditors who have not filed corresponding claims for a three-years period until the voting meeting if these measures endanger the introduction of the insolvency plan (Wilhelm, Richter and Lach, 2012, p. 5). Roland Berger confirms that more than 75% of practitioners have extensive knowledge of recent improvements in insolvency plan procedures and 36% conclude that changes have significantly improved the respective procedures (Moldenhauer and Wolf, 2017, pp. 14–20).

3.3 LEGAL FRAMEWORK FOR INSOLVENCY PROCEEDINGS IN GERMANY

Standard insolvency proceedings generally go through a certain lifecycle, which can be divided into five consecutive phases (Heesen and Wieser-Linhart, 2018, p. 25). Each phase follows a predefined legal scheme according to the current German Insolvency Statute. Figure 3.3 shows the standard phases of an insolvency.

Figure 3.3: Standard phases of insolvency proceedings
[Source: Author's representation based on Heesen and Wieser-Linhart (2018, p. 25)]

At the commencement of provisional insolvency proceedings, either the debtor or creditor must file a request with substantiated reasons (*Insolvenzordnung (InsO)*, 2020, Sec. 13; Krause, 2020, p. 339). Therefore, the opening of preliminary proceedings can be interpreted as asset protection until the proceedings are officially opened (Heesen and Wieser-Linhart, 2018, p. 25). In this phase, the existing assets are recognized and inventoried. The formation of an insolvency estate does not mean the conclusion of a company sale or immediate liquidation. According to Heesen and Wieser-Linhart (2018) and Madaus (2017), the recent changes in legislation promote a restructuring culture in Germany that focuses primarily on the survival of companies wherever possible (Madaus, 2017, p. 332; Heesen and Wieser-Linhart, 2018, p. 20). During these admissibility proceedings, the competent court shall investigate the grounds for insolvency proceedings (Bitzer, 2020, n. 102). After the official opening of insolvency proceedings by an injunction, the subsequent reporting meeting, also known as creditors' assembly, is one of the most essential milestones in a proceeding (Nickert, 2016). This meeting decides on the future of a company and decides whether a company is to be liquidated, sold in a transferred restructuring (asset deal), put into insolvency plan proceedings, or is continued under special procedures such as the self-administration and protective shield procedure (Nickert, 2016). In the distribution phase, the insolvency court agrees on discharging the residual debt and terminates the insolvency proceedings (Nickert, 2016). The following sections, in particular, outline the existing types of insolvency proceedings and provide further suggestions for the individual phases. Figure 3.4 summarizes the legislative framework for insolvency proceedings in Germany:

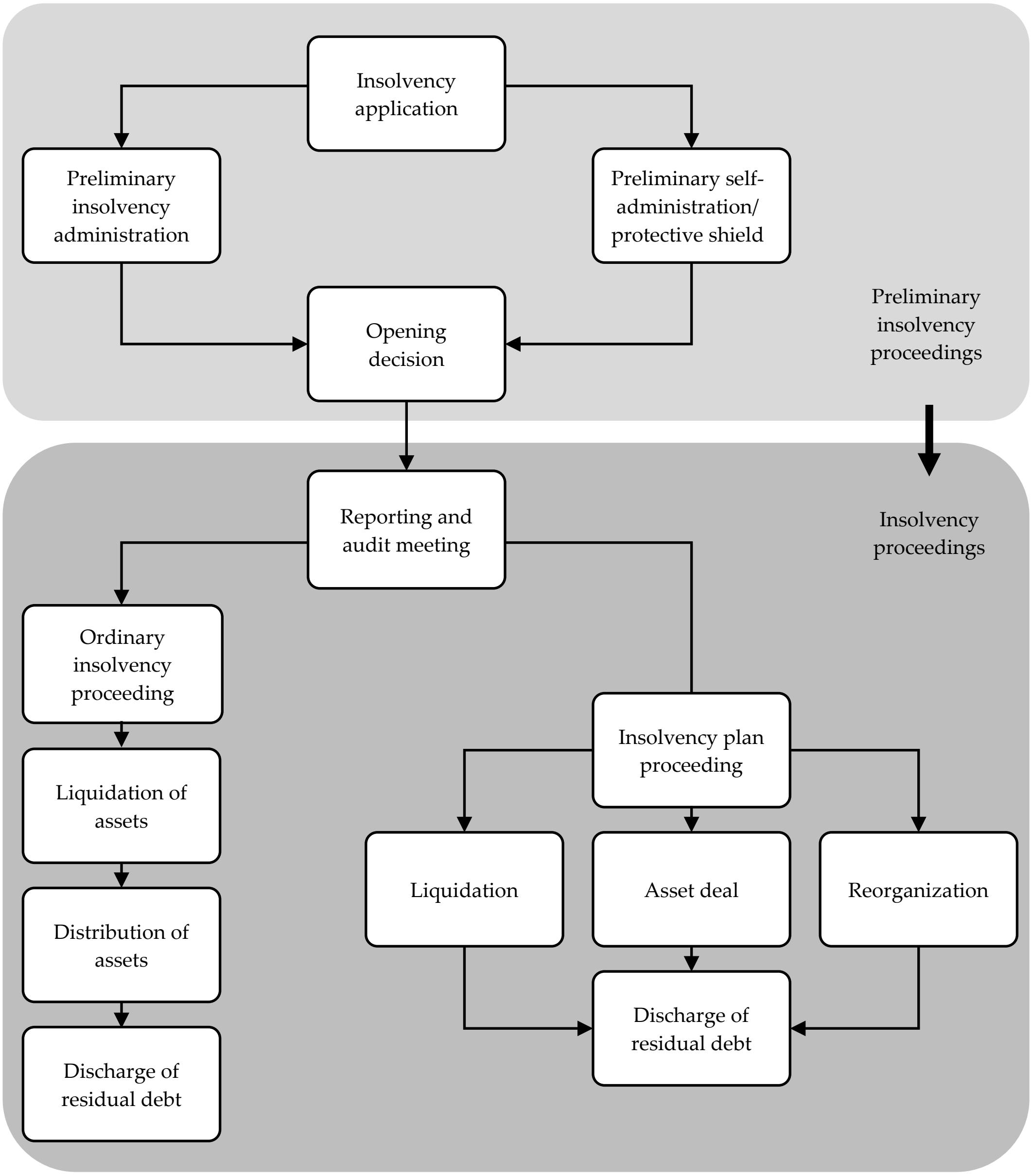

Figure 3.4: Overview of insolvency proceedings
[Source: Author's representation based on Heesen and Wieser-Linhart (2018, p. 25)]

3.3.1 Filing for insolvency

During the request phase, insolvency applications can be filed by debtors and creditors alike. However, all insolvency requests are only to be opened upon written application (*Insolvenzordnung (InsO)*, 2020, Sec. 13(1)). From a debtor's point of view, a complete list of all creditors and their claims, such as secured claims, claims of revenue administration, claims of the social insurance agencies, as well as claims from employee pension schemes, must be drawn up and submitted to the competent insolvency court (*Insolvenzordnung (InsO)*, 2020, Sec. 13(1)). In addition, the debtor must provide current financial and company-related data such as sales revenues, current balance sheet totals, number of employees in the previous financial year (*Insolvenzordnung (InsO)*, 2020, Sec. 13(1)). If an insolvency request is filed by a creditor, a profound legal interest, proof of certain claims, as well as a justification for the opening of insolvency proceedings, should be stated (*Insolvenzordnung (InsO)*, 2020, Sec. 14).

As explained in Section 3.1, the German Insolvency Statute forms the legal basis for insolvency proceedings and their definition. According to Part 1, Section 16, the opening requires a reason for insolvency. The Insolvency Statute defines three reasons for insolvency. If the first two compelling reasons for insolvency exist (inability to pay due obligations and overindebtedness), the management and majority shareholders of corporations are obliged to file an insolvency petition with the competent court within a period of 21 days in Germany (Heesen and Wieser-Linhart, 2018, p. 19).

3.3.2 Preliminary insolvency proceedings

After submission of the above written application to the competent court in charge, the filed request will be examined for its legal admissibility (Heesen and Wieser-Linhart, 2018, p. 19). If legal admissibility criteria are met, the competent court can initiate proceedings (Remmert, 2007, p. 2). In the event of opening proceedings, legal costs are incurred in the amount of approx. EUR 2,000 – 4,000 to be borne by the company concerned. If the assets are not sufficient to cover respective legal costs, the insolvency proceedings will be dismissed and the final liquidation of the company will be carried out (Heesen and Wieser-Linhart, 2018, p. 19). In short, reasons for insolvency and the coverage of legal costs make it possible to open proceedings (Nickert, 2016). The court therefore issues an order to open insolvency proceedings, which is the starting point of preliminary proceedings (*Insolvenzordnung (InsO)*, 2020, Sec. 27). According to the general principles of insolvency proceedings, the competent insolvency court "may hear witnesses and experts for this purpose" (*Insolvenzordnung (InsO)*, 2020, Sec. 5 (1)) in order to make its final decision. During this procedure of admissibility of possible insolvency grounds, which is also referred to as preliminary insolvency proceedings or preliminary administration phase, the competent court has the right to take protective measures until notification of the final decision within a period of two weeks and three months (*Insolvenzordnung (InsO)*, 2020, Sec. 28). Such protective measures may include the order of preliminary insolvency administration, suspension of enforcement as well as "the interception of the debtor's mail" (*Insolvenzordnung (InsO)*, 2020, Sec. 21 (4)). The competent court assigns a provisional insolvency administrator to supervise and manage the company's assets and to assume responsibility for the management's decision-making process (*Insolvenzordnung (InsO)*, 2020, Sec. 22). The provisional administrator may be appointed by the competent court as either a strong or weak insolvency administrator with regard to his decision-making and control powers (Leithaus, 2018, n. 3; *Insolvenzordnung (InsO)*, 2020, Sec. 22). A strong provisional insolvency administrator takes over administrative and dispositional power and leaves only a supportive role to the current management (Leithaus, 2018, nn. 7–9). If, on the contrary a weak provisional insolvency administrator is applied, the management's decision-making power remains with the current management. However, the weak insolvency administrator is granted extensive approval and control rights (Leithaus, 2018, n. 10). As regards liability, the insolvency administrator shall ensure that the value of the company is maintained (*Insolvenzordnung (InsO)*, 2020, Sec. 22). In case the insolvency administrator culpably violates due care and diligence in the insolvency proceeding, he may be held personally liable (*Insolvenzordnung (InsO)*, 2020, Sec. 60). The competent court decides on the type of insolvency administrator described above based on the current debtor situation and management structure (Heesen and Wieser-Linhart, 2018, p. 26). In addition, the establishment of a creditors' committee discussed in Section 3.2.1 represents a counterbalance to the power currently exercised by the provisional insolvency administrator.

In accordance with the aforementioned duration of the preliminary insolvency proceedings (*Insolvenzordnung (InsO)*, 2020, Sec. 28), it is important to emphasize the supporting insolvency compensation benefits. In Germany, the Federal Employment Agency (BA) replaces insolvency payments amounting to the full net wages for a time period of up to three months (Bundesagentur für Arbeit (BA), 2018). In case the company files for insolvency proceedings, respective compensation benefit claims are transferred to the Federal Employment Agency as insolvency creditor (*Insolvenzordnung (InsO)*, 2020, Sec. 55). In summary, this provided measure drastically reduces the personnel costs in a financial emergency and supports the company's ability to restructure. Heesen and Wieser-Linhart (2018) provide further input on insolvency substitutes, such as the financing of salaries through agreements on the cession of receivables with banks and finally substantiate the advantage of such measures in the context of restructuring (Heesen and Wieser-Linhart, 2018, p. 27).

3.3.3 Protective shield proceedings

The protective shield proceedings represent a special form of provisional self-administration which was introduced in 2012 as a major ESUG amendment, which is highlighted in Section 3.2.3. The conditions for opening preliminary protective shield proceedings depend on the economic situation of the debtor. In the event of impending insolvency or arithmetical insolvency with a positive going-concern assumption, restructuring is not pointless, and therefore, protective shield proceedings can be applied (Höher, 2012, p. 19). To apply for protective shield proceedings, the competent court must be presented with a certificate from an independent third party that proves the economic requirements (*Insolvenzordnung (InsO)*, 2020, Sec. 270b). After the formal opening of the proceedings, the competent court sets a deadline of three months for the submission of an insolvency plan (*Insolvenzordnung (InsO)*, 2020, Sec. 270b). At first sight, these measures do not differ from the self-administration procedure (Haas, Kolman, and Kurz, 2020, n. 21). However, in protective shield proceedings, the debtor appoints a qualified trustee and the safeguards implemented are less restrictive, such as no appointment of a provisional insolvency administrator or no general prohibition rights (Haas, Kolman, and Kurz, 2020, n. 23). Thus, the preliminary protective shield proceedings offer the debtor the possibility to prepare for a restructuring with similar possibilities as an insolvency plan procedure without a formal filing for insolvency (Heesen and Wieser-Linhart, 2018, pp. 27–28). From a practical perspective, restructuring measures such as liquidity, as well as financing planning, are discussed with stakeholders. Immediate restructuring measures, also known as *stop the bleeding*, as well as the choice of a qualified trustee, are typical examples of preparatory measures (Heesen and Wieser-Linhart, 2018, pp. 27–28).

According to Section 270b, the period for these preparatory restructuring measures is three months (*Insolvenzordnung (InsO)*, 2020, Sec. 270 b). After expiry of this period, the competent court shall agree on the opening of formal insolvency proceedings (Haas, Kolman, and Kurz, 2020, n. 22). The preliminary protective shield proceedings equip the debtor with an early restructuring tool, also known as *company voluntary arrangement*, to avoid formal insolvency proceedings (Haas, Kolman, and Kurz, 2020, n. 21). Nonetheless, the latest study by Roland Berger and HgGUR, which includes analyzing the effects of the preliminary protective shield proceedings, found that only 35% of all experts agree to a preferred and voluntary use of this restructuring measure, although more than 92% of participants confirm to be sufficiently informed about ESUG changes (Eschmann, Blatz, and Seagon, 2018, pp. 14, 22).

3.3.4 Self-administration

As an alternative to the insolvency plan proceedings, the option of self-administration was introduced and streamlined in the German insolvency estate as part of the ESUG modernization, which is also referred to as the Anglo-Saxon term *debtor-in-possession proceeding* (Poertzgen, 2020, p. 83). The debtor can file a request for self-administration. The competent court shall permit this special form provided that the circumstances do not result in disadvantages for the creditors involved (*Insolvenzordnung (InsO)*, 2020, Sec. 270). In this type of proceedings, the debtor manages the insolvency proceeding without an insolvency administrator (Haas, Kolman, and Kurz, 2020, n. 2). The debtor thus remains entitled to control and dispose of all assets concerned and conducts the business under the supervision of a court-appointed trustee (Hofmann and Giancristofano, 2018; *Insolvenzordnung (InsO)*, 2020, Secs. 270-285). The appointed trustee has the following tasks:

- to monitor the debtor's economic situation and management; in particular operating and private expenses (*Insolvenzordnung (InsO)*, 2020, Sec. 274 (2)).
- the implementation of the insolvency schedule and the valuation of registered claims (*Insolvenzordnung (InsO)*, 2020, Sec. 274 (3)).
- to monitor incoming cash-flows and, if necessary, approve outgoing payments if required (*Insolvenzordnung (InsO)*, 2020, Sec. 275 (2)).
- at the request of the creditors' assembly, certain transactions require the approval of the trustee (*Insolvenzordnung (InsO)*, 2020, Sec. 277 (1)).
- contestations of issues (*Insolvenzordnung (InsO)*, 2020, Sec. 280).

The combined actions carried out by an appointed trustee under self-administration underpin his supervisory role. At the same time, the management has control over all current business transactions. In addition, self-administration enables a more dynamic approach to insolvency, as no familiarization period is required compared to the insolvency administrator. Furthermore, it ensures business continuity, restructuring in protective shield proceedings as well as the financing of personnel costs through public insolvency subsidies (Heesen and Wieser-Linhart, 2018, p. 34).

3.3.5 Opening of insolvency proceedings

Within the scope of legal admissibility and taking into account expert opinions, the insolvency court initiates the insolvency proceedings by virtue of order (*Insolvenzordnung (InsO)*, 2020, Sec. 27). On the day of the opening, "the administration rights and rights of disposition are transferred to the insolvency administrator" (Nickert, 2016) in order to protect the assets from withdrawals. In the next step, the insolvency estate is formed. The insolvency estate can be described as the debtor's total assets when initiating the insolvency proceedings as well as assets accruing during the entire insolvency proceedings (Heesen and Wieser-Linhart, 2018, p. 20; *Insolvenzordnung (InsO)*, 2020, Sec. 35).

Subsequently, the insolvency proceedings will continue with the report and audit meeting, given that the insolvency administrator has not reported insufficient insolvent assets (*Insolvenzordnung (InsO)*, 2020, Sec. 26). The main objective of this meeting is to examine or reject the filed claims and to decide on the future of the company (Heesen and Wieser-Linhart, 2018, pp. 28–29). If there is no reasonable chance to restructure the company, ordinary insolvency proceedings will come into force. The primary objective of ordinary insolvency proceedings is the equal satisfaction of the creditor's claims by liquidating the debtor's assets (Hofmann and Giancristofano, 2018). On the contrary, both the reasons for restructuring and the willingness of the current debtor management to restructure allow for insolvency plan proceedings, the main aim of which is the continuation of the debtor's business operations (*Insolvenzordnung (InsO)*, 2020, Sec. 217). In the following section, the insolvency plan proceeding is presented in detail.

3.3.6 Course of the insolvency plan proceedings

According to Part 6, Section 218 (1), both the debtor and the insolvency administrator are authorized to file an insolvency plan to the insolvency court. The debtor's submission may be related to a request to open insolvency proceedings as described in Chapter 3.1 (*Insolvenzordnung (InsO)*, 2020, Sec. 218 (1)). For this purpose, a special discussion and coordination meeting will be announced and organized to vote for the prepared insolvency plan. The introduction of an insolvency plan aims to maximize the satisfaction of creditors by mutual agreement (Heesen and Wieser-Linhart, 2018, pp. 28–29).

The insolvency plan is composed of a declaratory and a constructive part (*Insolvenzordnung (InsO)*, 2020, Sec. 219). The insolvency plan details in the declaratory part measures already initiated or not yet implemented to inform all relevant parties (*Insolvenzordnung (InsO)*, 2020, Sec. 220 (1)). The declaratory part, in particular, symbolizes a roadmap with milestones that must be achieved in the insolvency proceedings. In the first part, there are no strict rules on the mandatory content to allow flexibility, as each insolvency case has its own characteristics (Rühle, 2020, n. 3). However, the declaratory part must contain all relevant information that is important for the creditors' decision when approving the plan as well as its final verification by the court (*Insolvenzordnung (InsO)*, 2020, Sec. 220). The actual restructuring plan is governed by the constructive part of an insolvency plan (*Insolvenzordnung (InsO)*, 2020, Sec. 221). In this part, the changes in the legal position of all parties involved are determined (*Insolvenzordnung (InsO)*, 2020, Sec. 221). According to Heesen and Wieser-Linhart (2018), exemplary measures in an insolvency plan for restructuring the company can include changes in the right of separation, waivers, partial sale of the company, deferral, plan monitoring, staff reduction, social plan, benefits in kind, or a debt-equity swap (Heesen and Wieser-Linhart, 2018, pp. 28–29). A detailed review of the measures proposed above will not be discussed further in this dissertation, as it does not fall within the scope of research. An introduction to a debt-equity swap was described in Section 3.2.4.

In order to meet the requirements of the rights of the individual creditor in the constructive part, set out in Section 221, creditor groups are formed which vote separately on the plan (*Insolvenzordnung (InsO)*, 2020, Sec. 243). The majority requirements listed below are necessary to formally accept an insolvency plan from the creditors (*Insolvenzordnung (InsO)*, 2020, Sec. 244):

(1) *The majority of creditors with voting rights and the sum of claims within a group must be reached and shall conclude a group vote.*
(2) *The majority of groups formed must agree to the proposed plan.*

The progress of group formation mainly overlaps with groups of creditors involved in insolvency proceedings. According to Hofmann and Giancristofano (2018), one can rank between five groups of creditors. First, secured creditors with full ownership of the assets can demand to be separated from the insolvency estate. Next, secured creditors with other security interests, such as assignments or mortgages, can participate in insolvency proceedings. Privileged creditors are characterized by an agreement reached with the insolvency administrator. It is important to mention that the insolvency administrator is personally liable for these types of claims. The largest group of creditors are the unsecured creditors, who generally receive a small quota on their requested claims. The last group is made up of subordinated creditors arising from shareholder loans or outstanding interest (Hofmann and Giancristofano, 2018).

Heesen and Wiener-Linhart (2018) essentially confirm the above-mentioned groups and extend the employees as an additional group to be included in an insolvency plan (Heesen and Wieser-Linhart, 2018, p. 31). After the entry of the ESUG in 2012, shareholders formed a separate group to vote on the draft insolvency plan, as they are directly affected by the restructuring instruments introduced, such as debt-equity swaps (Wilhelm, Richter and Lach, 2012, pp. 4–5).

Following the approval of the insolvency plan by the creditors and the debtors, the plan is finally confirmed by the competent insolvency court (*Insolvenzordnung (InsO)*, 2020, Sec. 248). Upon confirmation of the insolvency plan, the insolvency court is required to determine the termination of the insolvency proceedings (*Insolvenzordnung (InsO)*, 2020, Sec. 258).

The conditions for termination are fulfilled if the administrator settles acknowledged claims on the assets concerned and provides securities for rejected claims (*Insolvenzordnung (InsO)*, 2020, Sec. 258). In order to monitor the fulfillment of recognized claims, the insolvency plan may provide in its constructive part for measures to monitor the implementation of the plan (*Insolvenzordnung (InsO)*, 2020, Sec. 260). Upon the request of the debtors, the insolvency administrator as well as all creditors of the insolvency proceedings have to be heard at the final meeting (*Insolvenzordnung (InsO)*, 2020, Sec. 289). Subsequently, the insolvency court finalizes its decision on the residual debt discharge by way of a resolution (*Insolvenzordnung (InsO)*, 2020, Secs. 286–303).

In summary, the insolvency plan procedure has several advantages over ordinary insolvency proceedings. On the one hand, there is no change in the legal entity, which simplifies procedures relating to existing rent or lease agreements, licenses, certifications, or subsidies granted. On the other hand, an insolvency plan proceeding is a flexible proceeding with regard to its opening, as it can be opened within the framework of ordinary insolvency proceedings until the final meeting. The proposed procedure thus opens up creditor-friendly proceedings that should satisfy all parties equally (Heesen and Wieser-Linhart, 2018, p. 33). Figure 3.5 provides an overview of the insolvency plan proceedings:

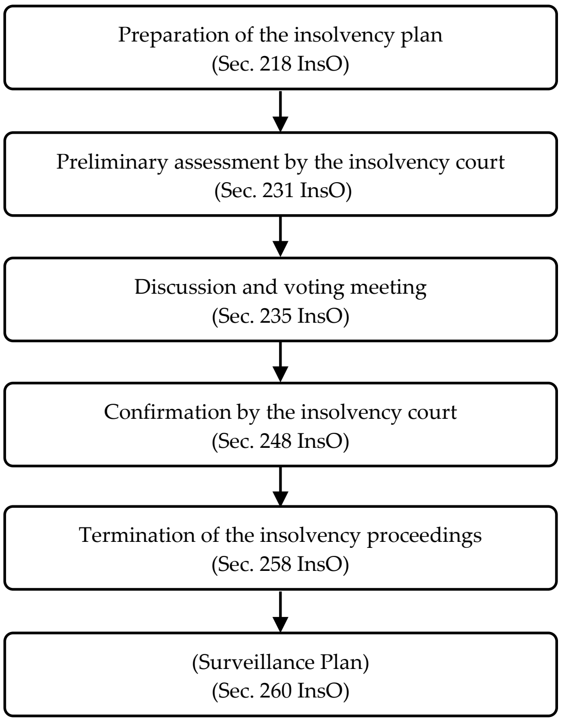

Figure 3.5: Flowchart of insolvency plan proceedings
[Source: Author's representation based on Heesen and Wieser-Linhart (2018, p. 30)

3.4 CONCLUSION

Since every PD model requires an exact definition of entrepreneurial failure to ensure the robustness and consistency of empirical findings, this dissertation applies the definition of the current German Insolvency Statute as a concise indicator for insolvency. The reason for opening insolvency proceedings is based on three insolvency grounds, which are explained in more detail in Chapter 3.1. In principle, the applicable legal statute distinguishes between the inability to pay the due obligations, overindebtedness, and impending insolvency. The first two out of three insolvency reasons require a mandatory insolvency petition, while the latter allows for voluntary insolvency proceedings. Nonetheless, the presented insolvency reasons of the current statute have been subject to punctual changes as temporary legal amendments and suspensions have been embedded in InsO throughout recent years, such as a temporary reformulation of the term overindebtedness based on Article 5 of FMStG in 2008 (Schunder, 2008, p. 695; Gundlach, 2020, n. 23) or the highly topical suspensions presented in COVInsAG (*COVID-19-Insolvenzaussetzungsgesetz (COVInsAG)*, 2020). Whereas the former transitional arrangement was later embedded in the current German Insolvency Statute (Gundlach, 2020, n. 23), the latter is still in progress and is therefore not part of the empirical investigation as the sample covers insolvencies from the years 2000 until 2018.

Other than that, in March 2012, the German legislators fundamentally reformed essential parts of the country's insolvency law with the implementation of the ESUG (Moldenhauer and Wolf, 2017, p. 2). The consideration of a uniform insolvency code is a decisive step in the methodological part. Thus, in Chapter 3.2, measures of the ESUG from 2012 are presented to provide a theoretical basis for further investigations in the empirical analysis.

Subsequently, the legal framework for insolvency proceedings in Germany is examined in the light of the above-mentioned changes in the law. In this context, a protective shield proceeding and self-administration are introduced and distinguished from the insolvency plan procedure.

4 DERIVATION OF THE RESEARCH METHODOLOGY

First, this chapter conceptualizes a systematic literature review of the development and improvements on various methodological approaches to bankruptcy forecasting, which is supported by additional findings in Appendix A-4.1, Appendix A-4.2 as well as Appendix A-4.3, respectively.[8] The primary aim is therefore to provide a differentiable understanding of four main statistical techniques found in the literature: (1) discriminant analysis models and related precursors, (2) logit regression and related statistical methods, (3) distance-to-default models, and (4) hazard models. Based on the findings of the literature review, logit models for binary data are presented before survival analysis is presented as the primary statistical method for this dissertation. In particular, non-parametric, parametric, and semiparametric approaches are described in detail. Having derived the extended version of the semiparametric Cox proportional hazards regression analysis as a preferred and promising approach, Chapter 4.4 shows appropriate measures to perform in-sample model diagnostics and to apply thorough tests to distinguish for out-of-sample model discrimination and out-of-sample out-of-time model calibration.

4.1 LITERATURE REVIEW

Various academics from the fields of accounting and finance have been actively involved in the investigation of corporate distress and the probability of default (PD). Using univariate discriminant analysis, Beaver (1966) pioneered the development of an empirical basis for insolvency prediction. Altman (1968) proposed a methodology using multivariate discriminant analysis (MDA) to

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[8] A streamlined version of the presented Chapter 4 has been published in: Ledwon, A. V. and Jäger, C. C. (2020) "Cox Proportional Hazards Regression Analysis to assess Default Risk of German-listed Companies with Industry Grouping", *ACRN Journal of Finance and Risk Perspectives*, 9(1), pp. 57–77. doi: 10.35944/jofrp.2020.9.1.005.

determine which ratios are useful in predicting insolvency, what weights should be given to these selected ratios, and finally, how the weights should be determined objectively (Altman, 1968, p. 591). In Germany, Perlitz (1973) and Baetge, Huß, and Niehaus (1988) were among the first to estimate and evaluate the performance of PD models using MDA.

In the 1980s, academics identified several econometric issues related to MDA, in response to its predominant use in the 1970s, which are discussed further in Section 4.1.2. As a pioneer, Ohlson (1980) proposed a less restrictive econometric approach to estimate PD models, using maximum-likelihood optimization of a logit function to capture the coefficients of predictor variables. Despite the fact that Altman and Hotchkiss (2006) suggest that logistic regression with a binary dependent variable is an appropriate approach to fit predictive models and assess default characteristics (Altman and Hotchkiss, 2006, p. 249),

> "one has to distinguish between single-period classification models, also named static models, and survival analysis. A contemporaneous trend in the bankruptcy prediction literature is the utilization of hazard models, where, contrary to static models, the time-to-default of a firm is captured, and hence more firm-year observations are incorporated to explain bankruptcy" (Ledwon and Jäger, 2020, p. 59).

The detailed statistical drawbacks of static models are explained in Section 4.1.4. Before an overview of the hazard models is given, distance-to-default (DD) models are presented, which outperform the static logistic models or MDA. Elsas and Mielert (2010) provide evidence for the discriminatory effect of the DD Model on the German stock market. Nonetheless, the exclusive use of market data in an option-based methodology disregards all other publicly available ratios, such as accounting information and macroeconomic data, as further discussed in Section 4.1.3. In summary, the academic literature on the prediction of corporate default is diverse, ranging from the univariate and multivariate discriminant analysis of the 1960s and 1970s to logit and probit of the 1980s, followed by contingent claims models and hazard methodology as part of survival analysis in the 2000s. Recent comparative studies confirm the superiority of hazard methodology in predicting the determinants and accuracy of corporate default (Campbell, Hilscher and

Szilagyi, 2008, pp. 2933–2935; Wu, Gaunt, and Gray, 2010, p. 45). Focusing on German literature, Schuhmacher (2006) develops a rating for German SMEs that confirms that a Cox proportional hazard model outperforms the static logit methodology for predicting defaults in terms of discriminatory power (Schuhmacher, 2006, p. 214). Mertens, Poddig, and Fieberg (2018), who focus on forecasting corporate insolvency in the German stock market, test different default risk models using manually retrieved data on German corporate defaults from Thomson Reuters Datastream (TDS), suggesting that the Campbell, Hilscher, and Szilagyi (2008) model performs better.

4.1.1 Discriminant analysis and precursors

Various academics in the fields of accounting and finance have actively dealt with corporate distress and bankruptcy. As one of the first, Beaver (1966) provides an empirical evidence in insolvency prediction by applying univariate discriminant analysis. He examined 30 ratios and concluded that cash flow to total debt was the most appropriate single ratio predictor (Beaver, 1966, p. 89). A later study by Beaver (1968) draws attention to the reaction of investors to earning announcements. He argues that changes in the price of common stocks have the effect of making investors rely on ratios as predictors of failure (Beaver, 1968, p. 192). Nevertheless, the univariate analysis fails to emphasize which ratios are essential for predicting bankruptcy (Altman, 1968, p. 591). It is therefore not appropriate to assess individual characteristics coherently (Altman, 1968, p. 591).

As a result, Altman (1968) developed the well-known Z-Score by applying Multiple Discriminant Analysis (MDA) based on 66 U.S. manufacturing companies from 1946-1965, half of which filed for bankruptcy under Chapter X, resulting in a 72% accuracy in predicting bankruptcy two years before the event (Altman, 1968, p. 600). MDA can be defined as:

> "a statistical technique used to classify an observation into one of several a priori groups dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form" (Altman, 1968, pp. 591–592).

The easy-to-use Z-Score has five linear ratios weighted with its coefficients as shown in Equation 4.1. However, Beaver's best single indicator for predicting cash flow in relation to total debt was not taken into account due to the lack of accurate data (Altman, 1968, p. 594).

$$Z = .012X_1 + .014X_2 + .033X_3 + .006X_4 + .999X_5, \tag{4.1}$$

where:

X_1 (WC/TA)= Working capital/total assets (%)

X_2 (RE/TA)= Retained earnings/total assets (%)

X_3 $(EBIT/TA)$= EBIT/total assets (%)

X_4 (ME/TL)= Market value of equity/book value of total liabilities (%)

X_5 $(Sales/TA)$= Sales/total assets (%)

Equation 4.1: Z-Score
[Source: Altman (1968, p. 594)]

In short, Altman's Z-Score takes into account asset-weighted ratios that reflect liquidity, profitability, enriched by solvency, leverage, and multidimensional measures (Altman and Hotchkiss, 2006, p. 239).

Deakin (1972) reproduced the MDA methodology proposed by Altman (1968). A random selection from 11 failed and 23 non-failed U.S. firms from Moody's industrial manual point out that the accuracy of the MDA decreases when estimating bankruptcy 4 or 5 years before occurrence. This finding was also observed in the earlier study by Altman (1968) (Deakin, 1972, pp. 168–170).

> "Multiple applications of MDA have been performed inter alia, by Edmister (1972), Blum (1974), Taffler & Tisshaw (1977), Taffler (1983). In summary, the conducted MDA models focused mainly on non-financial firms until the 1980s. Moreover, dominant samples included U.S. corporates and only a minority of studies investigated U.K. data (Taffler & Tisshaw, 1977) or small and medium-sized enterprises (SMEs) defaults (Edmister, 1972). Relevant studies on the performance of PD models utilizing the MDA approach for German firms have been initially

> estimated by Perlitz (1973) who performed one of the first MDA analyses for German-listed companies. Subsequently, Baetge, Huß and Niehaus (1988) contributed MDA for German firms with a set of three identified variables capturing a firm's capital structure, profitability and solvency" (Ledwon and Jäger, 2020, p. 58).

In addition to comparative studies in the field of MDA corporate failures, Altman's original Z-Score was further developed by Altman, Haldeman, and Narayanan (1977), covering a period of corporate bankruptcies between 1969-1975, to provide refinements in the implementation of the MDA technique due to academic controversy, economic changes of corporate observations, such as asset size and regulatory changes, i.e. changes in accounting standards (Altman, Haldeman and Narayanan, 1977, pp. 29–31). The updated sample consists of 53 U.S. bankrupt companies and 58 non-bankrupt companies. In addition, the originally formulated five-factor model was extended to a seven-factor model, as highlighted in Appendix A-4.3. The introduced ZETA™ model improves the accuracy rates with over 90% one year before and 70% up to five years before failure (Altman, Haldeman, and Narayanan, 1977, pp. 31–35). In particular, the cumulative profitability measure, calculated as retained earnings divided by total assets, is the most important variable that is measured univariately and multivariately. The actual coefficients for the ZETA™ model cannot be reported because of the proprietary nature of the ZETA™ model (Altman, Haldeman, and Narayanan, 1977, p. 39).

4.1.2 Logit regression and related statistical methods

The following section presents logit regression and related probit estimation approaches in the context of corporate distress and bankruptcy. In response to the predominant use of MDA in the 1970s, academics identified several econometric issues associated with MDA (Ohlson, 1980, p. 112; Zmijewski, 1984, p. 59). In that context,

> "first, statistical requirements such as comparable variance-covariance matrices and normally distributed predictors for both groups, of failed and non-failed firms, are

violated in MDA. Secondly, the output of an MDA model is a score with little intuitive interpretation. Lastly, the matching procedure typically used in MDA default prediction has been criticized to be arbitrary and hence falls within the topic of choice-based sample biases" (Ledwon and Jäger, 2020, p. 59).

Ohlson (1980) and Zmijewski (1984) proposed an alternative, less stringent approach to assessing the probability of default. Maximum-likelihood optimization is used to estimate the coefficients of predictor variables. Ohlson (1980) in particular performs logit regression to circumvent the above-mentioned problems associated with MDA (Ohlson, 1980, p. 112). An introduction to logit models for binary data is given in Section 4.2. No new ratios have been investigated in relation to the proposed variables. Nine independent variables were predominantly favored in the previous academic paper (Ohlson, 1980, p. 118). The established 9-factor O-score is shown in Equation 4.2.

$$O = -1.32 - .407X_1 + 6.03X_2 \text{-} 1.43X_3 + .0757X_4 - 1.72X_5 - 2.37X_6 - 1.83X_7 + .285X_8 - .5.21X_9, \tag{4.2}$$

where:

X_1 $(SIZE)$ = log(total assets/price-level index)

X_2 (TL/TA) = Total liabilities divided by total assets

X_3 (WC/TA) = Working capital divided by total assets

X_4 (CL/CA) = Current liabilities divided by current assets

X_5 $(OENEG)$ = One if total liabilities exceed total assets zero otherwise

X_6 (NI/TA) = Net income divided by total assets

X_7 (FU/TL) = Funds provided by operations divided by total liabilities

X_8 $(INTWO)$ = One if net income was negative for the last two years zero otherwise

X_9 $(CHIN)$ = $(NI_t - NI_{t-1})/(|NIt| + |NI_{t-1}|)$

Equation 4.2: Ohlson O-Score
[Source: Ohlson (1980, pp. 118–121)]

Ohlson (1980) derived the above coefficients on the basis of the logit model, which is based on 105 bankrupt firms under Chapter X or XI and 2,058 non-bankrupt firms. The reported default accuracies were 96.12%, 95.55%, and 92.84% for forecast windows within one year, two years, and one or two years, respectively (Ohlson, 1980, pp. 118–121).

Four years later, Zmijewski (1984) takes a very related approach to Ohlson (1980), which deviates only from the probability density function used. The estimated X-score model is based on a sample from 1972-1978 of 840 U.S. companies, 40 of which are classified as bankrupt (Zmijewski, 1984, p. 67). In the best case, an accuracy rate of 83.5% was correctly predicted (Zmijewski, 1984, p. 76). Financial ratios to measure corporate performance, leverage, and liquidity are included (Zmijewski, 1984, p. 72). However, the selection process of the predictors used is mainly based on their performance in previous studies. A detailed overview of the factors involved is given in Appendices A-4.1 and A-4.2. In the light of the academic contribution from Germany, "Behr & Güttler (2007) construct a logit scoring model ranging between 1992 and 2002 for estimating PD of German SMEs using a unique data set on SME loans in Germany to foster knowledge about their default risk and apply adequate cost of debt" (Ledwon and Jäger, 2020, p. 59). A comprehensive overview of relevant German studies is given in Appendix A-4.2.

4.1.3 Distance-to-default probability model

Distance-to-default (DD) comprises only data originating from the capital markets. Black and Scholes (1973) and Merton (1973) firstly introduced an approach in which the equity of the company can be regarded as a call option on the value of the company's assets. If the value of the assets is less than the nominal value of liabilities, i.e. the strike price, the call option is not exercised, and the bankrupt company is handed over to the debtors (Hillegeist et al., 2004, p. 8). The probability of bankruptcy is therefore embedded in the *Black-Scholes-Merton Probability of Bankruptcy* (BSM-Prob) (Hillegeist et al., 2004, p. 6). Variables used to evaluate BSM-Prob are the market value of equity, the standard deviation of return on equity, and total liabilities (Hillegeist et al., 2004, p. 6). Hillegeist et al. (2004) perform a discrete hazard model to measure the probability of bankruptcy and confirm biased estimates related to single-period logit models (Hillegeist et al., 2004, p. 22). Their sample consists of 78,100 company-year observations and 756 initial bankruptcies in the period 1980 to 2000 (Hillegeist et al., 2004, p. 7), which indicates that BSM-Prob contains significantly more information on the likelihood of bankruptcy compared to all accounting-based approaches (Hillegeist et al., 2004, p. 28). The comparison of the pseudo-R^2 of each model proves that "BSM-Score model (0.12) is 20% larger than for the O-Score[u] model (0.10) and is twice as large as the presudo-R^2 for the worst-performing model, Z-Score[u] (0.06)" (Hillegeist et al., 2004, p. 22). In addition, Elsas and Mielert (2010) provide evidence for the discriminatory effect of the DD Model on the German stock market with a mean out-of-sample AUC of 85% for 158 non-financial German insolvencies between the years 2000 to 2009 (Elsas and Mielert, 2010, pp. 24–25). Respective empirical results are further supplemented by a case study on Arcandor AG, validating high default rates in comparison to European peers (Elsas and Mielert, 2010, pp. 35–36).

Thus, stock market measures are a source of information on the probability of bankruptcy events that is not only based on publicly available information (Hillegeist et al., 2004, p. 6). However, reliance exclusively on market-based formulas to predict the default of companies, as is the case with BSM-Prob, is limited to fully efficient markets. Härdle et al. (2009) underpin this forecast obstacle, as it is primarily a question of knowing the market values of debt and equity (Härdle et al., 2009, p. 513). Therefore, fluctuations in stock and option prices imply fluctuations in assets to predict a market event such as a default, i.e. the decline in the value of assets below the value of a company's liabilities can be prone to error. Even in reasonably efficient markets, there is no guarantee that all relevant publicly available information on bankruptcy events is correctly priced, thus outweighing the potential benefits of the option-based approach (Hillegeist et al., 2004, pp. 6–7). Therefore, the following section focuses on hazard models that are more flexible in terms of explanatory data sources and take into account the statistical drawbacks of their predecessors.

4.1.4 Hazard models

Although Altman and Hotchkiss (2006) confirm that logit regression provided an "estimate of default between 0 and 1" (Altman and Hotchkiss, 2006,

p. 249), a distinction must be made between static models which consider only single-period classification and statistical techniques related to survival analysis.

> "A contemporaneous trend in the bankruptcy prediction literature is the utilization of hazard models, where, contrary to static models, the time-to-default of a firm is captured, and hence more firm-year observations are incorporated to explain bankruptcy. In current literature, the term hazard model is used interchangeably with relating terms such as panel logit model, pooled logit model, or Cox proportional hazards regression analysis with time-varying covariates" (Ledwon and Jäger, 2020, p. 59).

In short, the above terminologies can be summarized in the field of survival analysis (Ruppert, Wand, and Carroll, 2003, p. 323; Rodríguez, 2007b, p. 30).

Before providing empirical findings on survival analysis with regard to PD, three issues in relation to static logistic regression will be examined. From a theoretical and statistical perspective, the first issue relates to the selection bias and the second problem refers to the lack of the risk factor time. According to Shumway (2001), "static models ignore the fact that firms change through time and hence produce bankruptcy probabilities that are biased and inconsistent estimates of the probabilities that they approximate" (Shumway, 2001, p. 101). In summary, it should be noted that some firms file for insolvency proceedings as mature companies, while others fail shortly after foundation. Thus, company age is not taken into account in static models (Shumway, 2001, pp. 102–103). Finally, the third issue is the inefficiency of out-of-sample forecasts. Static models consider only one observation per company, i.e. the last available one. Consequently, it can be concluded that there is a bias in the sample selection, as the observations are not randomly selected. In contrast, the hazard models incorporate time series data for each company (Shumway, 2001, pp. 102–103, 111; Hillegeist et al., 2004, p. 20).

As suggested by Kiefer (1988) and Lancaster (1990), Shumway (2001) describes a hazard model as "a binary logit model that includes all available information to determine each firm's bankruptcy risk at each firm-year as a separate observation in time" (Shumway, 2001, p. 102). Thus, every company year observation is embedded in the database as long as the firm has not requested to file for bankruptcy. As a result, a company contributes only one failure observation (Shumway, 2001, p. 111). In Shumway (2001), all companies are categorized as bankrupt if they have filed for any form of legal bankruptcy proceedings in a five-year period of delisting. The sample collected contains 300 U.S. bankruptcies of 3,182 companies between 1962 and 1992 (Shumway, 2001, p. 114). Since the companies in the sample have many years of historical financial data available, the use of a hazard model leads to more accurate estimates and excellent forecasts compared to static models (Shumway, 2001, pp. 102–103). Therefore, hazard models solve the highlighted problems of static models and are well-suited for the analysis of data consisting of binary, time-series, and cross-sectional observations, such as data related to bankruptcy. It is related to the logit model (Hillegeist et al., 2004, p. 20). It is important to mention that hazard models group companies into a healthy group, and companies may leave this group for reasons other than insolvency. These events are known as censored observations (Shumway, 2001, p. 102). A detailed introduction to survival analysis is given in Section 4.3.

> "Shumway (2001) estimates his models based on independent variables from prior studies, such as the forecasting models by Altman (1968) and Zmijewski (1984). However, compared to static models, computed hazard models produce divergent statistical inferences as half of well-established utilized accounting ratios to forecast bankruptcy in previous studies are not statistically related to failure. Consequently, Shumway (2001) introduces new market-driven independent variables represented by relative size ($RSIZE$), past excess returns ($EXRET$) and idiosyncratic standard deviation of each firm's stock returns ($SIGMA$)" (Ledwon and Jäger, 2020, p. 59).

Company size has been identified as a key determinant, as the market capitalization of firms tends to be discounted prior to bankruptcy proceedings (Shumway, 2001, p. 115). Therefore, the $RSIZE$ has proven to be a crucial explanatory variable, calculated as the natural logarithm the market capitalization of each company at the end of the year preceding the year under observation in relation to the total size of the respective index (Shumway, 2001, p. 115). The second included market-driven variable is related to the above assumption. If the market capitalization of a company is affected before bankruptcy, its past excess returns also predict bankruptcy (Shumway, 2001, p. 115). $EXRET$ is defined as the past excess return of a company in year $t-1$ minus the value-weighted benchmark index return in year $t-1$ (Shumway, 2001, p. 115). The annual returns of each company are computed by cumulating monthly returns (Shumway, 2001, p. 115). If some of the monthly returns of a company are missing, the missing return is replaced by the value-weighted benchmark index return (Shumway, 2001, p. 115). The third market-driven variable introduced is $SIGMA$. According to Shumway (2001), $SIGMA$ is not only statistically but also logically closely linked to bankruptcy, as companies with highly volatile cash flows are more likely to be affected by bankruptcy. Consequently, Hillegeist et al. (2004) argue that "volatility is an important omitted variable in both the Altman (1968) and Ohlson (1980) bankruptcy prediction models" (Hillegeist et al., 2004, p. 6). In other words, $SIGMA$ metaphorizes the operative leverage (Shumway, 2001, p. 116). Consequently, the best out-of-sample forecasts are obtained using a hazard model that follows a hybrid approach of incorporating market-driven and accounting-based predictors for estimating bankruptcy with an accuracy rate of 75% in the first decile. (Shumway, 2001, p. 103).

As one of the rare academic contributions, Chava and Jarrow (2004) examine the effects of industry in a hazard rate model for U.S. firms. The respective sample consists of annual and monthly observation intervals from 1962 to 1999. In particular, the authors use an expanded database of 1,461 bankruptcies and again confirm the superior performance of Shumway's (2001) model compared to Altman (1968) and Zmijewski (1984) (Chava and Jarrow, 2004, pp. 537–538). The impact of industry estimating the hazard rate is examined for the following two reasons. First, the industries analyzed are confronted with different levels of competition, and second, these industries may have different accounting conventions, which implies industry-specific bankruptcy factors (Chava and Jarrow, 2004, pp. 538–539). In addition, the authors expand their investigation. Hazard rate models are extended to financial firms (Chava and Jarrow, 2004, p. 567). Monthly observation intervals are tested since most of the existing literature uses only annual observations due to data limitations (Chava and Jarrow, 2004, pp. 562–567). Chava and Jarrow (2004) improve bankruptcy prediction when using monthly observation intervals. As main findings, Chava and Jarrow (2004) conclude "that accounting variables add little predictive power when market variables are already included in the bankruptcy model" (Chava and Jarrow, 2004, pp. 537–538).

Beaver, McNichols, and Rhie (2005) apply hazard models to predict bankruptcy based on empirical suggestions by Shumway (2001) (Beaver, McNichols, and Rhie, 2005, pp. 93–94). The corresponding sample consists of U.S.-listed companies from 1962 to 2002, including 544 bankrupt non-financial companies as well as 4,237 non-bankrupt entities (Beaver, McNichols, and Rhie, 2005, pp. 8–9). A three-variable model is used, which focuses on three key elements of a company's financial strength. First, the return on total assets takes into account the profitability of a company. This ratio has proved to be a key parameter in previous empirical estimates. The second factor relates to Beaver's (1966) best single predictor cash-flow to total debt. Finally, the third variable is represented by total liabilities in relation to total assets, which is a leverage ratio (Beaver, McNichols, and Rhie, 2005, p. 98). A major difference to Shumway's (2001) model is that accounting-based variables have predictive power. Empirical results from Beaver, McNichols, and Rhie (2005) show that the models maintain the robustness of forecasts over time, while the predictive power of accounting-based variables decreases slightly. This effect is compensated by improving predictions of market-related variables (Beaver, McNichols, and Rhie, 2005, p. 118; Ledwon and Jäger, 2020, p. 60).

Campbell, Hilscher, and Szilagyi (2008) carry out the methodology of hazard models developed by Shumway (2001) and applied by Chava and Jarrow (2004). 800 U.S. bankruptcies between 1963 and 1998 are tested against various specifications (Campbell, Hilscher, and Szilagyi, 2008, p. 2906). The most powerful model follows a hybrid approach to market-based and accounting data. Furthermore, the authors introduce new variables with market adjustments, as highlighted in the following paragraph.

> "The conventional way of measuring total assets is based on book value. However, Campbell et al. (2008) measure the equity component of total assets at market value by adding the book value of liabilities to the market value of equities referred to as $NIMTA$. First, the authors argue that $NIMTA$ has stronger explanatory power, as

> market prices may include new information about the firm's prospects in more efficient and accurate manner" (Ledwon and Jäger, 2020, p. 60).

As a second measure, total liabilities are assessed in relation to total assets to provide a measure of leverage. $TLMTA$, a market-valued version of this accounting series, defined as total liabilities divided by the sum of market equity and book liabilities, outperforms the traditional book-valued series (Campbell, Hilscher, and Szilagyi, 2008, p. 2905). Third, Campbell, Hilscher, and Szilagyi (2008) construct $CASHMTA$, defined as cash and short-term investments relative to the market value of total assets to assess the liquidity position of a company. A high $CASHMTA$ level leads to high liquidity and consequently to a lower probability of filing for insolvency proceedings. Fourth, as a correction factor, the market equity of a company at the book value of equity, MB, is added to the final model, as the all above variables are adjusted to market values (Campbell, Hilscher, and Szilagyi, 2008, p. 2911). If book values are also statistically relevant, MB improves the ability to predict PD. Fifth, the log price per share of the firm, $PRICE$, is truncated above USD 15 (Campbell, Hilscher, and Szilagyi, 2008, p. 2906). Finally, $EXRETAVG$ is calculated as the excess return of the stock over the benchmark index, using geometrically decreasing weights $\emptyset = 2^{-\frac{1}{3}}$ in accordance with the literature (Campbell, Hilscher, and Szilagyi, 2008, p. 2911).

> "In summary, Campbell et al. (2008) demonstrate a reduced-form econometric model to predict corporate bankruptcies and failures at short and long horizons. The best model has greater explanatory power than the existing state-of-the-art models estimated by Shumway (2001) and Chava & Jarrow (2004) and includes the aforementioned additional variables with sensible economic motivation" (Ledwon and Jäger, 2020, p. 60).

In a subsequent part of the paper, the authors present evidence that the risk of failure cannot be adequately summarized by a measure of distance-to-default inspired by Merton's (1973) pioneering structural model (Campbell, Hilscher, and Szilagyi, 2008, pp. 2933–2935).

Mertens, Poddig, and Fieberg (2018) test various default risk models using manually retrieved data on German corporate defaults from TDS. In this context, the authors reassess the structural Merton distance-to-default (DD), the Z-Score by Altman (1968), and the hazard model by Campbell, Hilscher, and Szilagyi (2008) in a comparative study. Discriminatory power is measured using receiver-operating-characteristics (ROC) analysis. Furthermore, calibration tests and a loan market simulation are applied – proposals that Campbell, Hilscher, and Szilagyi (2008) achieve best-in-class results. "Although the performance evaluation metrics underpin that the failure score performs slightly worse when compared to U.S. data, the authors argue to use it as a benchmark default risk model for research as well as the industry" (Ledwon and Jäger, 2020, p. 60). Mertens, Poddig, and Fieberg (2018) advise against following Altman's (1968) Z-Score and the DD approach, as "the former has very weak discriminatory power and the latter is severely miscalibrated" (Mertens, Poddig and Fieberg, 2018, p. 29).

4.2 INTRODUCTION TO LOGIT MODELS FOR BINARY DATA

The logit model is essentially a regression model tailored to fit a binary dependent variable (Allison, 2012, pp. 1–2). A binary dependent variable is an example of a limited dependent variable (LDV). LDV is defined as a restricted dependent variable that lies between zero and one (Wooldridge, 2012, p. 583). Rodríguez (2007a) describes logit models as "appropriate when the response takes one of only two possible values representing success and failure, or more generally the presence or absence of an attribute of interest" (Rodríguez, 2007a, p. 1). Therefore, the application of Ordinary Least Squares (OLS) regression is not recommended since it yields firstly predicted probabilities beyond the restricted range [0;1] (Wooldridge, 2012, p. 257). Second, the use of OLS as a linear probability model implies a constant marginal effect of each explanatory variable occurring in its original form, and it includes heteroskedasticity (Wooldridge, 2012, pp. 257–258).

In accordance with the literature review carried out, a related form of logit regression represents a suitable approach for assessing the default risk. The logit model yields a binary score provided by an event of a company, in this case, an insolvency proceeding. In addition, the estimated coefficients can be interpreted individually by indicating the importance or significance of each of the independent variables in the explanation of the estimated PD. Logit methods (and probit techniques) use cumulative probability distributions to obtain a conditional probability of an observation belonging to a category (Wooldridge, 2012, pp. 584–586).

The statistical method dates back to the initial contributions by Goodman (1970), McFadden (McFadden, 1974), and Heckman (1978). In the context of this dissertation, a sample of companies that have survived a certain period and companies that have not, and dummy variables that take on a value of zero or one and represent the dependent variable, are collected. Theoretically, the dependent variable in logit models is also called Bernoulli or binary random variable (Wooldridge, 2012, p. 723). With respect to default, y_i is binary for company i under the assumption that only two values are coded as one or zero:

$$y_i = \begin{cases} 0, & for\ each\ company\ that\ survived\ a\ period \\ 1, & for\ each\ company\ which\ has\ filed\ for\ insolvency\ during\ a\ period \end{cases} \tag{4.3}$$

Equation 4.3: Bernoulli trial
[Source: Rodríguez (2007a, pp. 3–4)]

Therefore, y_i can be interpreted as a Bernoulli trial that is influenced by various independent factors, such as liquidity, profitability, and leverage as well as macroeconomic factors. y_i is thus a realization of a random variable Y_i, which can take the values one and zero with the probabilities π_i and $1 - \pi_i$, respectively. The distribution of Y_i is called the Bernoulli distribution with parameter π_i and can be written as (Rodríguez, 2007a, pp. 3–4):

$$Pr\{Y_i = y_i\} = \pi_{i_i}^{y_i}(1 - \pi_i)^{1-y_i} \tag{4.4}$$

Equation 4.4: Bernoulli distribution
[Source: Rodríguez (2007a, pp. 3–4)]

Since y_i can only take values of 0 or 1, one can conclude y_i = 1, which leads to π_i and y_i = 0, which leads to 1 - π_i.

The introduction of the logit transformation ensures that the estimated response probabilities are strictly between zero and one, as shown in Figure 4.1.

The transformation of the values of the discrete binary dependent variable of logistic regression is visualized in an S-shaped curve, also known as a logistic curve, which represents the probability of an event. Therefore, the logistic curve is nonlinear, since the probability of an event must approach [0;1] but is never outside these limits. Thus, although the midrange has a linear component, the probabilities flatten out as they approach the lower and upper probability limits [0;1] and become asymptotic to these limits (Hair Jr *et al.*, 2014, p. 315).

$$\eta_i = logit(\pi_i) = log\frac{\pi_i}{1-\pi_i} \tag{4.5}$$

Equation 4.5: Logit transformation
[Source: Rodríguez (2007a, p. 6)]

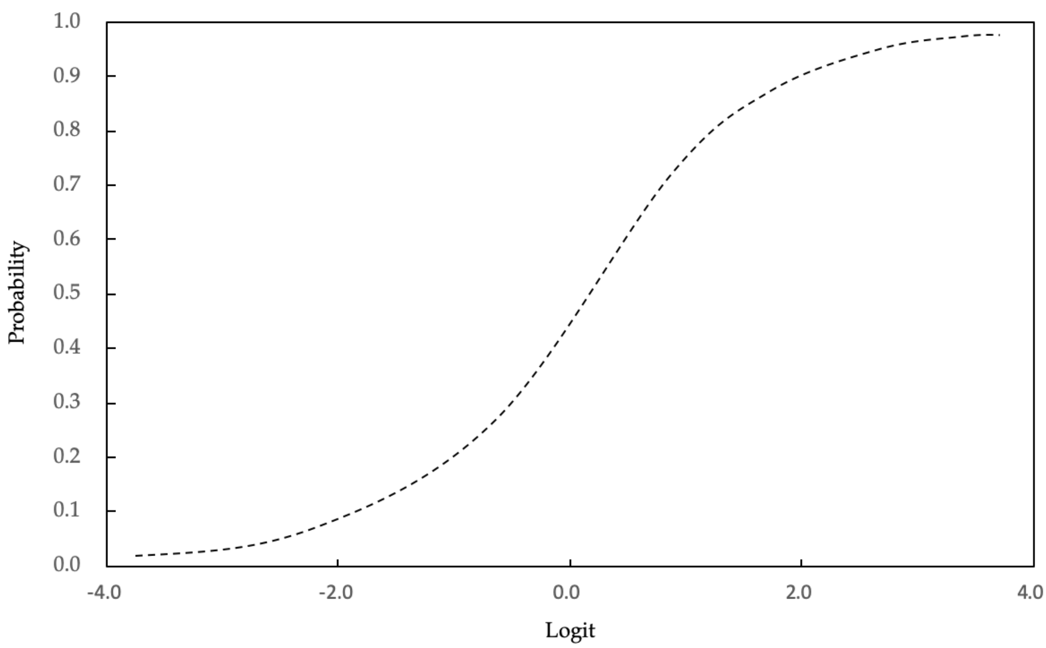

Figure 4.1: Logit transformation
[Source: Author's representation based on Rodríguez (2007a, p. 7)]

Next, considering the systematic structure of a logistic regression model, x_i as observed covariates and β as vectors of regression coefficients are presented.

$$logit(\pi_i) = x_i\beta \tag{4.6}$$

Equation 4.6: Generalized linear model with binomial response and logit link
[Source: Rodríguez (2007a, p. 7)]

The final solution for the probability π_i in the logit model presented in Equation 4.6 provides the logistic function that ensures that each coefficient is assessed separately to keep other variables constant (Wooldridge, 2012, pp. 584–586).

$$\pi_i = \frac{\exp(x_i\beta)}{[1 + \exp(x_i\beta)]} \tag{4.7}$$

Equation 4.7: Logistic function in the logit model
[Source: Wooldridge (2012, p. 585)]

For the estimation of the coefficients β_0 ... + β_k of LDV models, maximum likelihood estimation (MLE) is essential. One reason for using MLE is that it automatically takes heteroscedasticity into account (Wooldridge, 2012, p. 587). The logistic regression is strictly between zero and one, the log-likelihood function $\mathcal{L}(\beta)$ is highlighted in Equation 4.8, where π_i depends on the covariates x_i and a vector of parameters β by the logit transformation described in Equation 4.6.

$$\mathcal{L}(\beta) = \sum_{i=1}^{n} \{y_i log(\pi_i) + (n_i - y_i) log(1 - \pi_i)\} \tag{4.8}$$

Equation 4.8: Maximum likelihood estimate
[Source: Rodríguez (2007a, p. 10)]

To test the statistical significance of the derived logit model, the Wald Test, or Likelihood Ratio, is used (Rodríguez, 2007a, pp. 9–16). The derivation of the logistic regression model presented forms the theoretical basis for the survival analysis presented in Chapter 4.3. A modification of the survival analysis is indispensable to predict the probability of default and the covariates influencing it. Since survival analysis is superior to static logistic regression, the methodology is described in more detail.

4.3 SURVIVAL ANALYSIS

Static logistic regression, as presented in Chapter 4.2, examines responses that assume one of only two possible values for success and failure, or as general rule, the existence or non-existence of an interest attribute (Rodríguez, 2007a, p. 1). Nonetheless, static logistic regression is not able to provide details on how success or failure is related to the intrinsic time effects of a well-defined event such as insolvency (Shumway, 2001, p. 101). In addition, censored observations are neglected. For some firms, therefore, the event of interest had not yet taken place at the time the data were examined, and the time-dependency effect of explanatory variables in relation to their survival time is disregarded (Rodríguez, 2007b, p. 1). As a result, "static logistic regression is less effective in assessing the default risk predictors" and "an alternative and promising approach, which has been primarily used in biostatistics and lately in financial credit risk literature, constitutes survival analysis" (Ledwon and Jäger, 2020, p. 60). Survival analysis is an approach that analyzes data where the time to event is of particular interest. In the literature, the response is referred to as *failure time*, *survival time*, or *event time* (Columbia University, 2004, p. 1). "For simplification and standardization, the terminology '*survival analysis*' is utilized, referring to the event of interest as '*default*' and to the waiting time as '*survival time*'" (Ledwon and Jäger, 2020, pp. 60–61).

Censoring mechanisms are an essential aspect of censored regression models in the case of survival analysis (Wooldridge, 2012, p. 611). In this context, the following paragraph distinguishes censoring mechanisms in order to provide the theoretical basis for left and right censoring as well as for Type I and Type II. For censoring Type I, one can assume a sample of n units, which are given for a fixed time t (Moore, 2016, p. 3). In other words, the time frame of the analyzed sample is fixed and limits the maximum potential observation time τi for $i = 1, \ldots, n$ (Wooldridge, 2012, p. 609). This fixed censoring may be due to institutional constraints, such as the decision to determine the start of the study carried out after the InsO came into force in 1999 in such a way that the comparability of the defaults is controlled. Moreover, τi may be different for each unit of observation but is nevertheless fixed and restricted in advance (Rodríguez, 2007b, p. 6). According to

Rodríguez (2007b), "the fact that the duration is fixed may be an important practical advantage in designing a follow-up study" (Rodríguez, 2007b, p. 6). An incomplete type of observation may occur in the left or right tail of the time axis and is defined as left- and right-censored, respectively (Hosmer, Lemeshow, and May, 2011, pp. 6–8). Right-censoring occurs when an observation unit leaves the study before an event occurs, or the study ends before the event has occurred (Lunn, 2007, p. 2). Hosmer, Lemeshow, and May (2011) consider right-censored data as the most common type of censoring (Hosmer, Lemeshow, and May, 2011, p. 9). In practice, some observations units may leave the survival study within τi without experiencing default due to mergers and acquisitions (M&A), squeeze-outs, voluntary delisting, and other corporate measures, and other firms may encounter the default event after τi. An observation is defined as left-censored if the event of default already occurred before τi (Lunn, 2007, p. 2; Hosmer, Lemeshow and May, 2011, p. 8). Practically, this includes all insolvency proceedings before the observation time τi. In contrast, censoring of Type II requires the number of defaults d to be defined in advance. Therefore, the assumption of a sample of n units, which is followed until d units have experienced the event of default, defines Type II censoring. Logically, the total duration of the study is random and is unknown in advance (Rodríguez, 2007b, p. 6). Figure 4.2 illustrates left and right censoring within the Type I mechanism, as this type is available for the conducted empirical analysis. Cases C and E do not fall within the scope of the investigation, in which left- and right-censoring is clearly described within Type I censoring.

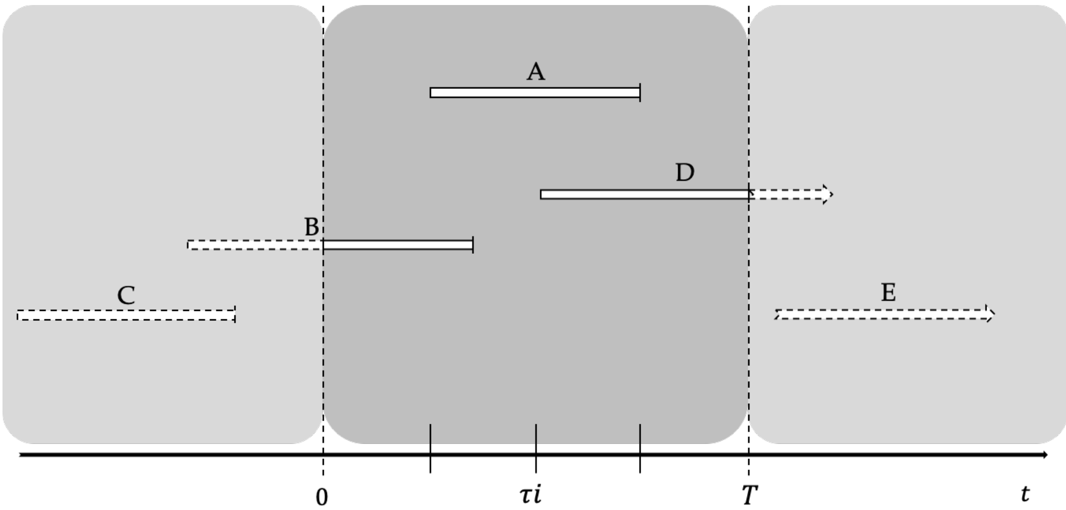

Figure 4.2: Censoring mechanism Type I

[Source: Author's representation based on Hoyer (2011, p. 73)]

The modeling of survival analysis requires the determination of a discrete time scale that reflects the event of default in intervals (Hosmer, Lemeshow, and May, 2011, p. 17). "Although insolvency dates have been tracked as exact dates, annual data intervals have been selected due to the following reasons. Discrete time of intervals of one year ensures comparability of accounting-, market-based- and macroeconomic indicators" (Ledwon and Jäger, 2020, p. 61). As highlighted in the literature review in Chapter 4.1, annual intervals were chosen to predict corporate insolvencies and at the same time to allow comparability with existing studies. "Hence, the estimation of the survival function is based on 19 consecutive yearly intervals denoted as $[t_0; t_1]; [t_1; t_2]; \dots; [t_{18}; t_{19}]$. Every firm i joining the study at observation time t_0 is categorized as active" (Ledwon and Jäger, 2020, p. 61). Consequently, companies that enter the German stock market after t_0 are also active companies. With respect to the default, $y_{i,t}$ is binary for company i at time t, under the assumption that binary values are coded as one or zero. If the default is documented, a change of state, i.e. $y_{i,t}$ = 1 is only observed in the year of the respective default. Therefore, companies are not taken into account in the year following the event. "Likewise, a firm that survives to the last period t_{19} cannot have failed in previous periods and thus does not change its state from zero to one" (Ledwon and Jäger, 2020, p. 61). The inclusion of right-censored data is essential since this type of observation contributes information until dropout to the likelihood function (Hoyer, 2011, p. 75).

4.3.1 Non-parametric models for survival data

The following section assumes a homogeneous population, disregarding heterogeneity of various risk factors that affect the corporate default, which is dealt with in the following chapter. First, two methods for estimating the survival distribution are presented. On the one hand, the survival function $S(t)$ defines the probability to survive up to a point t (Moore, 2016, p. 11).

$$S(t) = P(T > t) \tag{4.9}$$

Equation 4.9: Survival function
[Source: Moore (2016, p. 11)]

In the literature, the survival function is also defined as the hazard function $h(t)$, also known as the intensity function or the magnitude of mortality (Moore, 2016, p. 11).

$$h(t) = \lim_{\delta \to 0} \frac{P\big(\mathrm{t} < \mathrm{T} < \mathrm{t} + \delta \big| \, \mathrm{T} > \mathrm{t}\big)}{\delta} \tag{4.10}$$

Equation 4.10: Hazard function
[Source: Moore (2016, p. 11)]

The hazard function can be described as the probability that a company will survive to time t and change its state to a state of default, before disappearing in time interval δ, divided by the length of this interval (Moore, 2016, pp. 11–12).

Non-parametric survival analysis can be formulated in discrete time intervals to reflect the event of default. One way of graphically representing the survival function $S(t)$ is therefore the Kaplan-Meier estimator, first proposed by Kaplan and Meier (1958), which is the most commonly used and simple method of calculating survival over time, despite all the difficulties associated with issues or situations (Kaplan and Meier, 1958; Gijbels, 2011, pp. 709–710). The Kaplan-Meier estimator, also known as product limit estimator, presents empirical probabilities of survival, i.e. companies that have not opened insolvency proceedings within the specified 19 time intervals $[t_0; t_1]; [t_1; t_2]; \ldots; [t_{18}; t_{19}]$ or are subject to censoring (Moore, 2016, p. 25). Taking into account the ranked time intervals t_j and the respective risk number denoted by n_j, as well as the observed number of defaults for each set interval d_j, the Kaplan-Meier estimator of the survival function at the time is:

$$\hat{S}(t) = \prod \frac{n_j - d_j}{n_i} \tag{4.11}$$

Equation 4.11: Kaplan-Meier estimator
[Source: Hosmer, Lemeshow, and May (2011, p. 22)]

The Nelson-Aalen estimator, constructed by Nelson (1969) and Aalen (1978), is a non-parametric estimator of the cumulative hazard rate function for censored data or incomplete data. Cumulative hazard refers to the concept of time discrete default. The terminology *cumulative* is used to describe the fact that its value is the total sum of the hazard up to time t (Hosmer, Lemeshow, and May, 2011, p. 62). In mathematical terms, the cumulative hazard is referred to as:

$$\hat{h}(t) = \sum \frac{d_j}{n_i} \tag{4.12}$$

Equation 4.12: Nelson-Aalen estimator
[Source: Hosmer, Lemeshow, and May (2011, p. 60)]

The proposed estimators, represented by Kaplan-Meier estimator for survival functions and Nelson-Aalen estimator for cumulative hazard rate, are part of non-parametric or descriptive survival analysis. The primary objective of such an analysis is a thorough analysis of the sample and event variables in order to assess basic time-related data aspects. To illustrate the relationship between the survival probability and hazard rate by way of example, one can first consider a high initial hazard (A and C), which describes a high mortality rate of observations in early life, whereas the opposite is demonstrated by a low initial hazard (B and D) (Moore, 2016, p. 12).

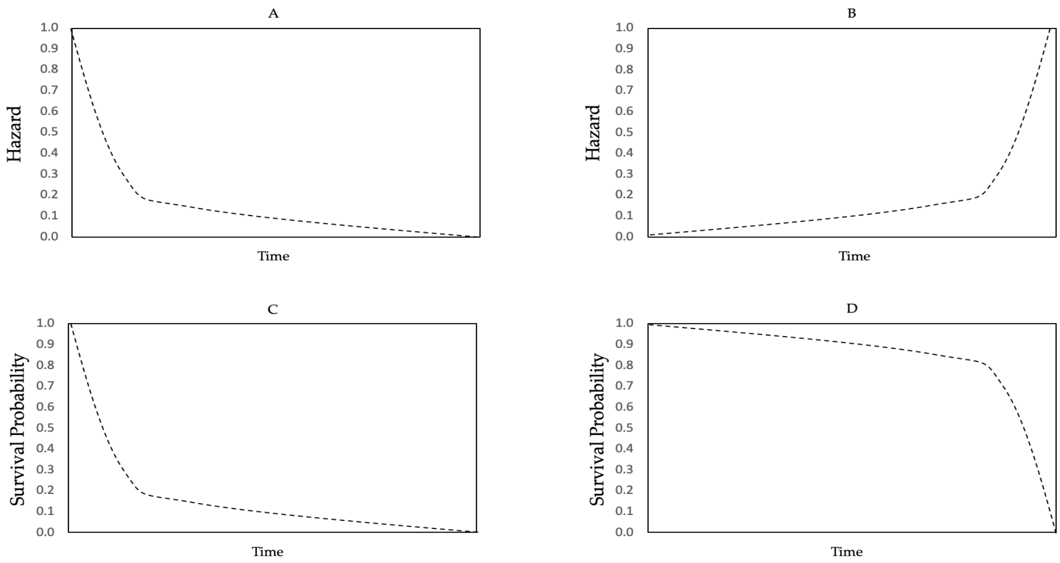

Figure 4.3: Hazard and survival functions
[Source: Author's representation based on Moore (2016, p. 12)]

However, a non-parametric approach is not sufficient for the objective of investigating defaults and related factors affecting the insolvency of companies listed in Germany. Therefore, the following chapter begins with the introduction of a baseline hazard rate to take into account parameters that influence default. After establishing the theoretical foundations, parametric and semiparametric hazard regression will be discussed in order to decide which of the presented methods is more advantageous for the purposes of this dissertation. In summary, non-parametric models are used as a part of non-parametric data analysis in Section 5.2.2 and are further presented in Appendix A-5.1, Appendix A-5.2, and Appendix A-5.3

4.3.2 Parametric regression models for survival data

The primary goal of parametric survival analysis is typically based on an investigation of the relationship of the survival distribution to covariates (Fox and Weisberg, 2018b, p. 1). The aim of a fully parametric survival model is to characterize the hazard as an explicit function of time as well as to study covariates (Hosmer, Lemeshow, and May, 2011, p. 68).

This section introduces a class of survival analyses called parametric models since the distribution time until the event is assumed. Examples of distributions commonly used for survival time are the Weibull, log-logistic, lognormal, and generalized gamma model (Kleinbaum and Klein, 2005, p. 292).[9] According to Hoyer (2011), the application of a parametric survival model is advisable if decisions on the distribution of a sample can be formulated a priori. In addition, all the above models are limited in terms of simplified assumptions for modeling time dependence (Hoyer, 2011, p. 83).

Zhang (2016a) concludes that one of the most popular forms of the parametric regression model is the Weibull regression model because it provides an estimate of the baseline hazard function as well as allows explanatory variables to be included. However, due to the predefined assumption of a scale parameter, Weibull regression models are used less frequently in the literature compared to the semiparametric proportional hazard approaches (Zhang, 2016a, p. 1). For illustration, the specification of the Weibull model is given in Equation 4.13.

$$h(t, \mathrm{X}) = \alpha t^{\alpha-1} exp(\beta' \mathrm{X}) \tag{4.13a}$$

$$= \alpha t^{\alpha-1} \lambda , \tag{4.13b}$$

Equation 4.13: Weibull model
[Source: Jenkins (2005, p. 26)]

where $\lambda = \exp(\beta' \mathrm{X})$, $\alpha > 0$, and $\exp(.)$ is the exponential function $\alpha > 1$, indicates a monotonically increasing hazard rate over time while decreasing hazard rates are present when $\alpha < 1$. If $\alpha = 1$, there is a constant hazard rate and the Weibull distribution becomes an exponential distribution (Jenkins, 2005, p. 26).

Subsequently, semiparametric regression models for survival data are presented and differentiated accordingly to extract a best-fit methodology for the purposes of this dissertation. As a starting point, it is essential to show how a regression model-like structure can be integrated into the hazard function (Hosmer, Lemeshow, and May, 2011, p. 67). In other words, "the hazard function,

[9] For an overview of parametric survival and hazard functions, see Kleinbaum and Klein (2005, p. 295).

used for regression in survival analysis, can lend more insight into the failure mechanism than linear regression" (Columbia University, 2004, p. 4). In the previous chapter, hazard functions were defined simply as a function of survival time, while the addition of an extra dimension to the specification allows the hazard rate to vary between individuals, depending on their characteristics (Jenkins, 2005, p. 25). The dependence of the hazard rate on observable independent covariates can be described as a proportional hazard model.

The proportional hazard function is the product of two functions (Hosmer, Lemeshow, and May, 2011, p. 69), where $h_0(t)$ is a baseline hazard function indicating the risk of default, and $\exp(x_i\beta)$ is the relative risk associated with the set of explanatory covariates x_i (Rodríguez, 2007b, p. 11). By using an exponential function, the non-negativity of hazard rates (Hoyer, 2011, pp. 82–83), as well as great flexibility in the choice of regression variables, are guaranteed (Kalbfleisch and Prentice, 2002, p. 96).

4.3.3 Semiparametric regression models for survival data

This section focuses on the methodologies of relative risk or Cox proportional hazard regression model. As already discussed, parametric models assume a known failure time distribution, with the exception of a parameter vector. Therefore, relative risk models allow for more flexibility compared to strictly parametric models. Relative risk models include a non-parametric feature as they involve an undetermined function by means of an arbitrary baseline hazard function (Kalbfleisch and Prentice, 2002, p. 95).

Furthermore, this model type also includes parametric model aspects since it offers modeling the failure rate and its relation to a set of explanatory covariates (Kleinbaum and Klein, 2005, p. 108). This type of methodology is therefore often referred to as a semiparametric model (Kalbfleisch and Prentice, 2002, p. 95). In summary, compared to a parametric approach, semiparametric models allow more flexibility in estimating a baseline hazard function since, in the latter, the shape of the hazard function must be determined a priori.

The Piecewise-Constant Exponential (PCE) model is an example of a semiparametric continuous-time hazard specification presented in the following paragraph (Jenkins, 2005, p. 38). In contrast to parametric models, the PCE specification does not fully characterize the form of the hazard function, and therefore, it is not specified a priori but is determined by data (Jenkins, 2005, pp. 38–39). The idea underlying the PCE models is that survival time can be divided into discrete time intervals, each of which assumes that the hazard rate is constant over time (Jenkins, 2005, pp. 38–39). The PCE model must be distinguished from the Cox proportional hazard model. Both are continuous-time models, can contain time-varying covariates, and allow some flexibility in the form of the hazard function (Hoyer, 2011, p. 88). However, the Cox model is more general in that it allows the derivation of estimates of the slope parameters in the vector, regardless of what the baseline hazard function looks like (Hoyer, 2011, p. 88). The PCE model requires the specification of cutpoints, while the Cox model estimates are derived for a completely arbitrary baseline hazard function (Jenkins, 2005, p. 40).

Therefore, the next section presents the Cox proportional hazards regression model, originally proposed by Cox in 1972.

> "The Cox proportional hazards regression model comprises both a non-parametric aspect in the sense that it involves an unspecified function in the form of an arbitrary baseline hazard function, denoted as $h_0(t)$, and parametric model characteristics, as it allows modeling of the relationship between the failure rate and explanatory covariates (Cox, 1972)" (Ledwon and Jäger, 2020, p. 61).

This type of methodology is therefore often referred to as a semiparametric model (Kalbfleisch and Prentice, 2002, p. 95). A common equation of the Cox proportional hazards regression model can be described as follows:

$$h(t, \mathbf{X}) = h_0(t)\exp\left[\sum_{i=1}^{p} \beta_i X_i\right], \tag{4.14}$$

where $h(t, \mathbf{X})$ is the expected hazard at time t for an entity with a given specification of a set of explanatory variables, indicated by the bold $\mathbf{X} = (X_1, X_2, \ldots, X_p)$. The baseline hazard function is called $h_0(t)$, and $\exp\left[\sum_{i=1}^{p} \beta_i X_i\right]$

represents the relative hazards, where the sum is across the p explanatory time-independent covariates $\mathbf{X}$.

Equation 4.14: Cox proportional hazards model
[Source: Kleinbaum and Klein (2005, p. 244)]

Since time-independent variables for a given observation remain constant over time, the following section presents a model setup that takes into account both time-independent and time-dependent variables whose values differ over time. Modeling such a survival analysis requires the establishment of a discrete time scale that reflects the occurrence of defaults, defined as intervals (Hosmer, Lemeshow, and May, 2011, p. 17). For this reason, an extended version of the proportional hazards regression model taking into account the Andersen-Gill counting process (AG-CP) is required. With a view to extending the model, start/stop intervals for each company-year observation are considered (Andersen and Gill, 1982). Consequently, several observations per identifier are specified in the data setup. To take into account the correlation within each identifier, a cluster variance is used, which is provided by the argument $cluster(IDENT)$.

One can extend the Cox proportional hazards regression model to include both time-independent and time-dependent explanatory covariates:

$$h\big(t, \mathbf{X}(t)\big) = h_0(t)\exp\left[\sum_{i=1}^{p_1} \beta_i X_i + \sum_{j=1}^{p_2} \delta_j X_j(t)\right], \tag{4.15}$$

where $h\big(t, \mathbf{X}(t)\big)$ is the expected hazard at time t for a company with a given specification of a set of time-independent explanatory variables $\mathbf{X}(t) = \big(X_1, X_2, \ldots, X_{p1}\big)$, denoted by X_i, and time-dependent explanatory variables $\mathbf{X}(t) = \big(X_1(t), X_2(t), \ldots, X_{p2}(t)\big)$ denoted by $X_j(t)$.

The baseline hazard function is called $h_0(t)$ multiplied by the exponential function $\exp\left[\sum_{i=1}^{p_1} \beta_i X_i + \sum_{j=1}^{p_2} \delta_j X_j(t)\right]$.

Equation 4.15: Extended Cox proportional hazards model
[Source: Kleinbaum and Klein (2005, p. 249)]

The formula for the Cox model likelihood function is based on a partial likelihood (PL) estimation method, not on maximum likelihood (Jenkins, 2005, p. 77). As defined by Kleinbaum and Klein (2005),

> ”the term ’partial’ likelihood is used because the likelihood formula considers probabilities only for those subjects who fail, and does not explicitly consider probabilities for those subjects who are censored. Thus the likelihood for the Cox model does not consider probabilities for all subjects, and so it is called a ‘partial’ likelihood” (Kleinbaum and Klein, 2005, p. 113).

Since the Cox model allows a detailed analysis of determinants of corporate default, the estimates are derived on the basis of a completely arbitrary baseline hazard function (Hoyer, 2011, p. 88). For this reason, the extended Cox proportional hazards regression analysis, taking into account the AG-CP, is carried out in this dissertation in Chapter 5.3.

4.4 MODEL DIAGNOSTICS, DISCRIMINATION, AND CALIBRATION

Prior to presenting the selected model diagnostics as well as appropriate discrimination and validation techniques, one should be aware of the misconceptions and fallacies about the p-value which recently regained scientific attention (Dirnagl, 2019, p. 2421). According to Hirschauer et al. (2016),

> “The p-value is often considered as the gold standard in inferential statistics. The standard approach for evaluating empirical evidence is to equate low p-values with a high degree of credibility and to refer to findings with p-values below certain thresholds (e.g., 0.05) as *statistically significant*. [However], researchers’ fixation on obtaining statistically significant results may introduce biases and increase the rate of false discoveries. Misinterpretations of the p-value as well as the introduction of bias through arbitrary analytical choices (*p-hacking*) have been critically discussed in the literature for decades" (Hirschauer et al., 2016, p. 558).

Albeit numerous issues related to the misconceptions and misuses of the p-value have been documented (Greenland et al., 2016, p. 337), the following paragraph concentrates on three main issues. First, the sample size plays a crucial role when applying p-values for-in-sample regression results. As demonstrated by

Kim and Bang (2016), a larger number of observations may lead to relatively smaller p-values, also referred to as "the well-known 'large N→small P' phenomenon" (Kim and Bang, 2016, p. 76). Second, data transformation, which is not sufficiently justified by the relevant literature may indicate the issue of *p-hacking,* where a desired statistical significance level is aimed to be achieved which potentially translates in an overestimation of the empirical evidence (Hirschauer et al., 2016, p. 565). Third, the intentional removal or inclusion of exogenous variables within a regression model may result in misleading empirical findings as the final selection is not adequately backed by the economic intuition and may face omitted-variable bias (Hirschauer et al., 2016, p. 566).

In light of the aforementioned issues related to the use of p-values, Nuzzo (2014) suggests to report additionally confidence intervals to enhance the quality of statistical significance reporting (Nuzzo, 2014, p. 152). Halsey (2019) supports this view and refers to confidence intervals as "vital information" for providing robust and thorough empirical reporting (Halsey, 2019, p. 3).[10] Apart from statistical measures, the data collection and adjustment process should be presented more transparently to allow for robust findings when using p-values (Vidgen and Yasseri, 2016, p. 4).[11] Nonetheless, there is the necessity for other measures than p-values and confidence intervals, such as out-of-sample model discrimination and model quality tests (Kim and Bang, 2016, p. 79). As a result, the following chapter presents appropriate techniques to mitigate the aforementioned issues and achieve the research objectives in this dissertation.

Model-diagnostic measures are carried out to analyze whether adapted Cox regression models in this dissertation adequately explain the exemplified results (Fox and Weisberg, 2018a, Chap. 8). For this purpose, the first proportional hazards (PH) assumption, influential observations, or outliers, as well as nonlinearity, are presented theoretically.

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[10] This dissertation applies lower .95 and upper .95 confidence intervals in parentheses for presented in-sample results presented in Chapter 5.3.3.

[11] A thorough and transparent documentation of data collection and adjustment is presented in Chapter 5.2.

In addition to model diagnostics, accurate default prediction models show significant discrimination and calibration. Discrimination can be defined as the "ability to separate defaulters from non-defaulters", while calibration focuses on "the ability to make unbiased forecasts" (Blöchlinger, 2012, p. 1089). In the light of model discrimination measures, the receiver operating characteristic (ROC) curve and its complementary area under the curve (AUC) estimate are presented, focusing on the time-dependent AUC ratio. Finally, the state-of-the-art walk-forward procedure according to Sobehart, Keenan, and Stein (2000) is introduced as the main calibration measure. This rational and stringent out-of-sample out-of-time testing provides the theoretical basis for a decile ranking, which is applied in Section 5.4.3.

4.4.1 Model diagnostics

Model diagnostics help to specify whether fitted Cox regression models in this dissertation adequately explain the presented results (Fox and Weisberg, 2018a, Chap. 8). Three types of diagnostics are then applied:

(1) *Testing the proportional hazards (PH) assumption*
(2) *Detecting influential observations or outliers*
(3) *Examining nonlinearity*

In order to evaluate the preceding aspects of model diagnostics, residuals are investigated. A residual is calculated for each observation and each firm delivering a measure of the difference between actual and predicted values (Fox and Weisberg, 2018a, Sec. 8.6.1). Three main types of residuals are used in this dissertation. First, scaled Schoenfeld residuals are calculated and visualized to investigate the proportional hazards (PH) assumption. Second, deviance residuals test influential observations and outliers. Third, Martingale residuals indicate nonlinearity.

Cox (1972) formulated that the effect of a covariate does not change over time. This assumption also applies to time-dependent covariates. The observed effect of the covariate is assumed to be constant, although values may change (Grant, Chen, and May, 2014, p. 356). The PH assumption can be verified using statistical tests, namely by assessing scaled Schoenfeld residuals and graphical diagnostics based on the same approach (Zhang et al., 2018, pp. 5–7). In summary, Schoenfeld residuals are independent of time. A plot showing a non-random pattern against time shows the evidence for the violation of the PH assumption (Zhang et al., 2018, pp. 5–7). In addition to the graphical diagnostics, a p-value derived from a normal standard statistic is also given for each variable. This p-value is used to more objectively assess the PH assumption for each variable in an adjusted model. A non-significant p-value, greater than 0.10, indicates that the PH assumption applies, while a small p-value of less than 0.05 indicates that the tested variable does not satisfy this assumption (Kleinbaum and Klein, 2005, p. 166). In addition to the per-variable tests, a global chi-square test, also referred to as the Schoenfeld global test, is usually performed and provides a single GOF test statistic (Kleinbaum and Klein, 2005, p. 167).

Another essential aspect of model diagnostic is a graphical examination to detect outliers and influential data points that could have a significant impact on selected coefficients. For this purpose, dfbeta/dfbetas, and deviance residuals can be plotted (Hosmer, Lemeshow, and May, 2011, p. 184; Fox and Weisberg, 2018b, p. 16). These tests illustrate the estimated changes in the coefficients divided by their standard errors (Fox and Weisberg, 2018a, Sec. 8.3.3). Finally, Martingale residuals can be plotted against covariates to examine nonlinearity (Fox and Weisberg, 2018b, p. 16). In other words, Martingale residuals assess the functional form and fit of covariates, and thus the variable and model fit.

4.4.2 Model discrimination

With regard to GOF and the assessment of model adequacy, a measure analogous to R^2 could be of interest as a criterion of model performance for Cox's proportional hazards regression analysis. For linear regression analysis, R^2 is defined as "the proportion of the sample variation in the dependent variable explained by the independent variables" (Wooldridge, 2012, p. 104) and "allows … to test a group of variables to see if it is important for explaining y" (Wooldridge, 2012, p. 81). By definition, R^2 is represented by a number between zero and one, where a higher value of R^2 indicates that more variation is explained by the model, up to a maximum of 1 (Wooldridge, 2012, p. 80). A straightforward application comparable to R^2 in linear regression is, however, difficult due to censored observations (Müller, 2004, p. 1). Especially for binary response models, pseudo R^2, such as proposed by McFadden (1974) among others, can be used to ensure model comparison. However, the Cox proportional hazards regression takes censored data into account. According to a comparative empirical study by Schemper and Stare (1996), which compares the performance of R^2 for proportional hazards regression models, there is no comparable, useful, and well-established measure for a proportional hazards regression model based on censored data. As a result, no further information on the GOF measure R^2 is given, as this is not within the scope and the validation aim of this dissertation.

Alternatively, the receiver operating characteristic (ROC) curve is a statistical measure that evaluates the discriminatory power of a binary variable while yielding an output that is easy to interpret (Krzanowski and Hand, 2009, p. 12). If we concentrate on the research question in this dissertation, the binary variable insolvency is explained by a set of independent predictors that influence the validity of a formed statistical model. By definition, the ROC curve may be explained as "a plot of true-positive rate (TPR) on the y-axis versus false-positive rate (FPR) on the x-axis in relation to a cut-off threshold" (Krzanowski and Hand, 2009, p. 12), designated as C. Table 4.1 gives an overview of possible decision results for a cut-off value C. The true-positive rate (TPR) answers the question when the actual classification is positive, i.e. when an insolvency application is filed, and as a result, how often the classifier predicts the status of insolvency. The false-positive rate (FPR) assesses when the actual classification is negative, i.e. a company does not file for insolvency, and how often the classifier wrongly predicts a positive outcome of insolvency (Engelmann, Hayden, and Tasche, 2003, p. 6).

Table 4.1: Decisions results considering the cut-off value C

This table illustrates the true-positive rate (TPR) and the false-positive rate (FPR) in relation to a cut-off threshold C for evaluating the ROC curve.

		Insolvency	**No Insolvency**
PD model	below C	TPR	FPR
	above C	FPR	TPR

[Source: Representation based on Engelmann, Hayden, and Tasche (2003, p. 6)]

The performance of a PD model is influenced by the cut-off value C and its ROC curve shape. This means that the higher the area under the ROC curve (AUC), the greater the discriminatory power of the fitted PD model (Engelmann, Hayden, and Tasche, 2003, p. 6). In academic literature, AUC is frequently equated with concordance, also known as C-statistics (Wang, 2014, p. 2108; Harrel Jr., 2015, p. 318). Since a ROC curve is a two-dimensional representation of classifier performance, AUC allows classifiers to be compared in a single scalar value that illustrates expected model performance (Fawcett, 2006, p. 868). The AUC is 0.5 for a random model without substantial discriminative power and is 1.0 for an ideal model (Engelmann, Hayden, and Tasche, 2003, p. 6). Therefore, an appropriate AUC ratio is between 0.5 and 1.0 for any sensible PD model.

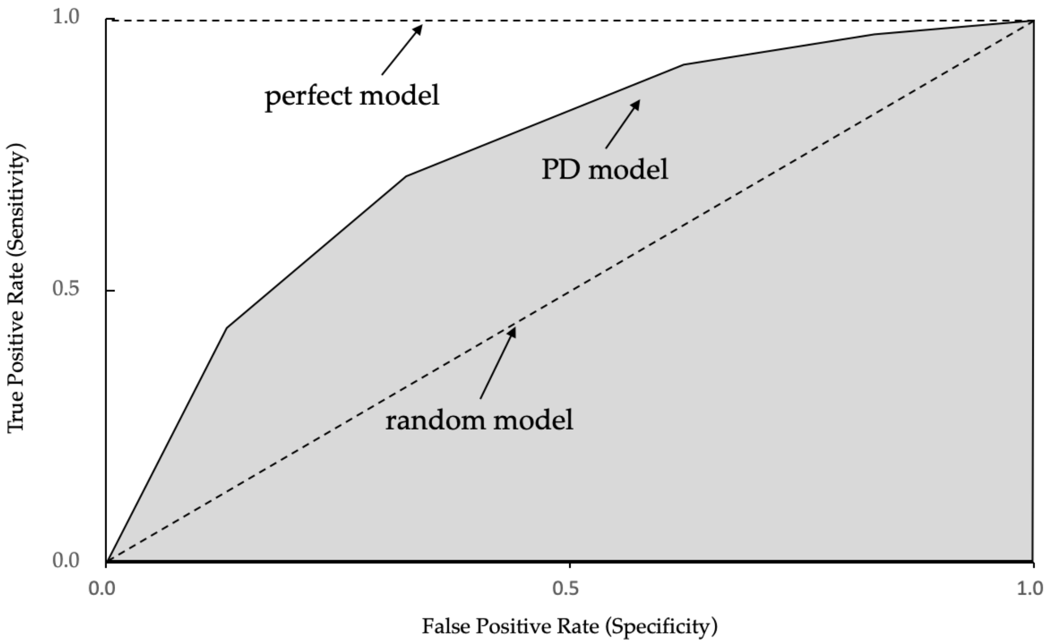

Figure 4.4: Receiver operating characteristic (ROC)
[Source: Author's representation based on Engelmann, Hayden, and Tasche (2003, p. 7)]

In summary, the AUC curve analysis assesses the discriminatory power of a statistical model between companies that file for insolvency and companies that are considered active and affected by right-censored data.

> "However, the traditional approach of AUC curve analysis considers the event [insolvency] status and marker value for a firm as fixed over time. Thus, the essential factor default is not considered in terms of discriminatory power. In consequence, companies that are financially stable in an early stage of the study may file for insolvency at a later stage due to longer study follow-up. Thus, an AUC ratio as a function of time is more appropriate" (Ledwon and Jäger, 2020, p. 62).

Nonetheless, academics focusing on German PD literature predominantly use the standard AUC curve approach.

The applied AUC ratio in this dissertation is modified to enable time-dependency and censoring since both aspects have an influence on the estimation results of the survival curves and the coefficients of survival regression model

(Chambless and Diao, 2006, p. 1). In particular, a dynamic AUC is performed for the right-censored time-to-event data proposed by Chambless and Diao (2006).

In-sample calculated AUC can artificially boost and distort discriminatory results, "the easiest solution is to estimate the predictive model on a training sample and to test it on an independent evaluation sample" (Lieli and Hsu, 2019, p. 102). As applied in Section 5.4.2 the dataset, "is divided into training and testing samples with a 70% to 30% data partition. The *iauc* summary is given by the integral of AUC at [1,19] weighted by the estimated probability density of the time-to-event outcome" (Ledwon and Jäger, 2020, p. 62). To test the hypotheses, this dissertation uses a nonparametric Wilcoxon rank-sum test for dependent samples.

4.4.3 Model calibration

As "insolvency is a relatively rare event among publicly traded German firms, a rigorous out-of-sample out-of-time calibration procedure, also known as walk-forward testing" (Ledwon and Jäger, 2020, p. 62) is a key validation technique of this dissertation. The advanced walk-forward procedure, according to Sobehart, Keenan, and Stein (2000), provides rational and accurate out-of-sample tests for the predictive power of various prediction models.

In a real-world application of a default forecasting model, "walk-forward testing provides a framework for generating statistics that allow researchers to test the predictive power of a model on data not used to fit it" (Stein, 2007, p. 94). Before the approach is clearly visualized, the procedure is presented descriptively for one period. Therefore, for reasons of simplification, the example below refers to the year 2002. First and foremost, a Cox regression model will be fitted to cover all available data until 2002. "Once the model's form and parameters are established for the selected time period" (Ledwon and Jäger, 2020, p. 62), forecasts will be made based on all company-year observations available in the next year 2003. These forecasts of PDs per company-year observation join the result set. Subsequently, the estimation window is shifted forward by one year, i.e. for the year 2003. Therefore, all data available from 2000 to 2003 are now used for model fit. Fitted models are then utilized to predict estimated values for 2004. This process is repeated, with new predictions being adding to the result set each year. In summary, the walk-forward procedure follows a widening estimation window (Ledwon and Jäger, 2020, p. 62).

Figure 4.5 highlights the above testing approach. Whereas in-sample data is visualized by dark circles, out-of-sample out-of-time testing data is represented by white circles. The test results for each year of prediction are collected to generate a set of results that forms the basis for a performance evaluation. According to Stein (2007), "this approach simulates, as closely as possible given the limitations of the data, the process by which the model will actually be used. Each year, the model is refit and used to predict the credit quality of firms one year hence" (Stein, 2007, p. 94). The advantages resulting from the walk-forward analysis are not only an appealing and realistic approach to data calibration, but also reparametrized models on a periodic assumption offer information on economic changes that are of specific interest to practitioners (Stein, 2007, p. 95).

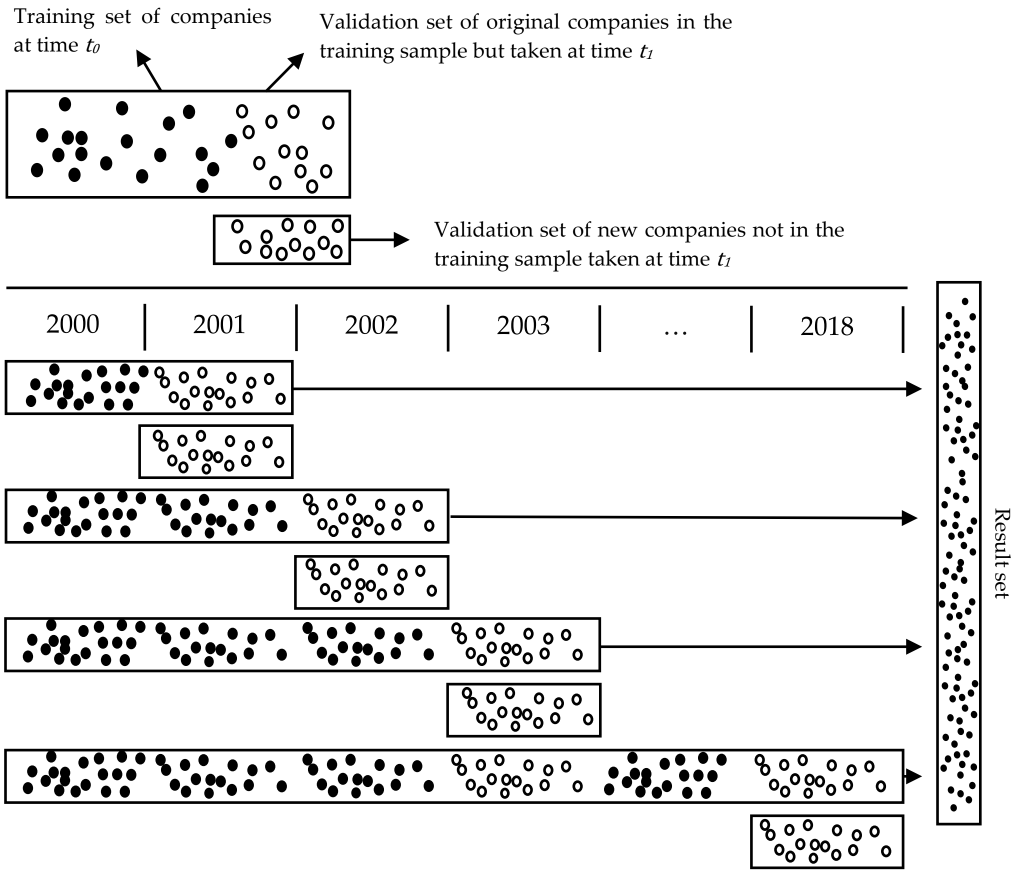

Figure 4.5: Diagram of the walk-forward testing approach
[Source: Author's representation based on Sobehart, Keenan, and Stein (2000, p. 9)]

Following Shumway (2001) and Chava and Jarrow (2004), Section 5.4.3 introduces a decile ranking based on the objectively generated result sets, in which accuracy rates (AR) of correctly predicted insolvencies are calculated in an out-of-sample out-of-time validation study.

4.5 CONCLUSION

Chapter 4.1 provides a comprehensive literature review focusing on the relevant streams of academic contributions to the modeling of corporate default. A wide range of approaches, largely based on international and U.S. literature, is expanded by corresponding research on the German market.

After the introduction of logit models for binary data in Chapter 4.2, this dissertation derives survival analysis as a suitable research method for empirical analysis. Based on the conducted literature review, non-parametric, parametric, and semiparametric approaches are presented in Chapter 4.3. In view of the formulated research objectives of this dissertation, the first non-parametric Kaplan-Meier and Nelson-Aalen estimators are used in the empirical part in Section 5.2.2 as part of descriptive statistics. The semiparametric Cox proportional hazards regression, taking into account the AG-CP, is used as the main econometric regression model to create a PD model for non-financial German entities in Section 5.3.1.

Finally, Chapter 4.4 presents model diagnostics as well as the discrimination and validation criteria that are indispensable for the presentation of PD models. According to Stein (2007),

> "a model without sufficient validation is only a hypothesis. Without adequate objective validation criteria and processes, the benefits of implementing and using quantitative risk models cannot be fully realized. This makes reliable validation techniques crucial for both commercial and regulatory purposes" (Stein, 2007, p. 77).

5 EMPIRICAL ANALYSIS

In this chapter, theory-based hypotheses are developed and operationalized, which are to be tested and evaluated. The main objectives are to derive the importance of accounting and financial ratios as well as industry effects, which are helpful in uncovering potential insolvencies. When applying enhanced semiparametric Cox proportional hazards regression analysis[12], the stepwise variable selection procedure with forward and backward iterations aims to statistically improve the empirical results of adjusted PD models and to present the best candidate final regression model. Finally, the effects on the introduction of the ESUG is quantitively tested in accordance with its objectives, namely to enter insolvency proceedings in a healthier state.

Before introducing the sample that forms the basis for the unbalanced panel structure of this empirical analysis, the following sections demonstrate the nature of data adjustment measures, a non-parametric survival analysis of the event variable, and a deep immersion in industry classifications. The independent variables collected were significant predictors of corporate defaults in earlier empirical research and are described in detail in Section 5.2.3.

The main part of the empirical analysis consists of in-sample empirical results and GOF measures, which are subsequently supplemented by comprehensive out-of-sample discrimination and validation tests. Finally, a benchmark analysis in Chapter 5.5 focuses on summarizing the findings and relating them to previous studies identified in the literature review conducted.

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[12] The empirical investigation of Model (1) – Model (3) and the inclusion of industry variables has been published in: Ledwon, A. V. and Jäger, C. C. (2020) "Cox Proportional Hazards Regression Analysis to assess Default Risk of German-listed Companies with Industry Grouping", *ACRN Journal of Finance and Risk Perspectives*, 9(1), pp. 57–77. doi: 10.35944/jofrp.2020.9.1.005.

Figure 5.1 gives an overview of empirical research design; bold arrows show the structure of related chapters and dashed arrows indicate how the sections are combined to investigate research objectives.

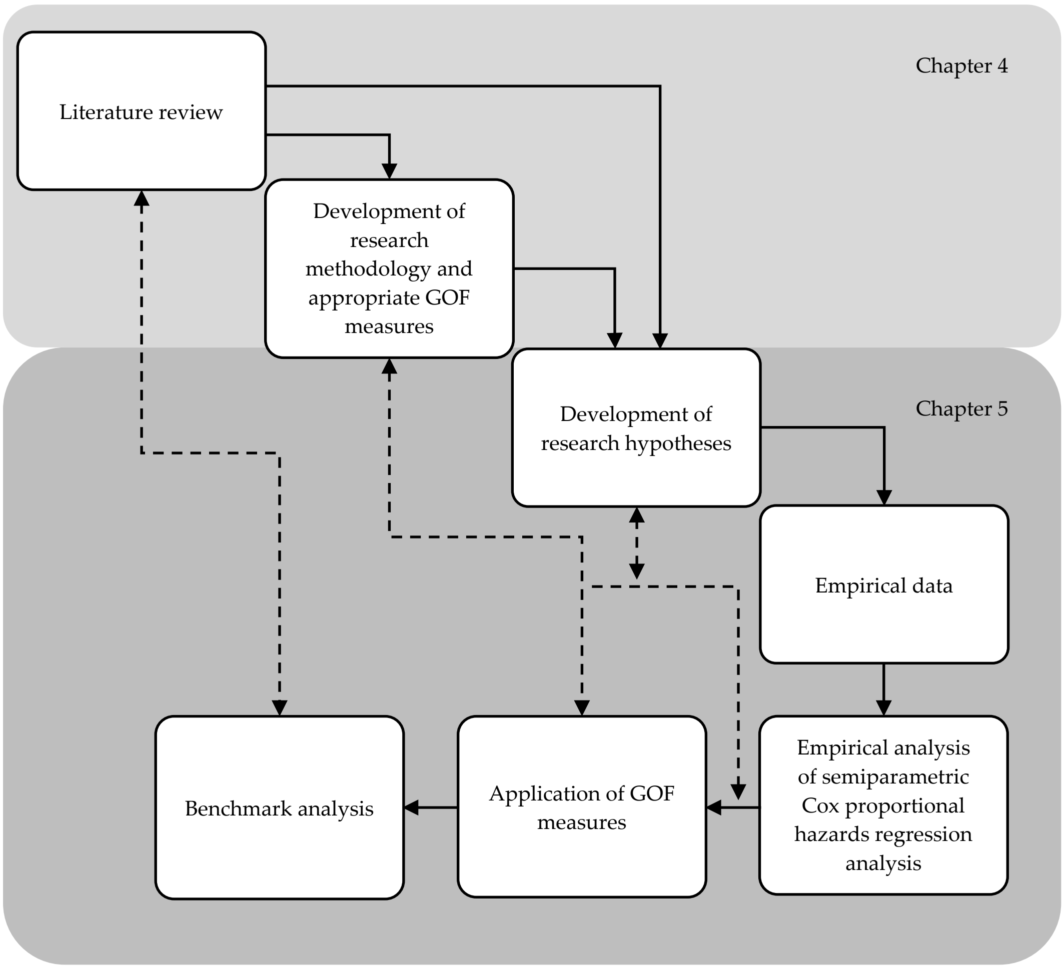

Figure 5.1: Empirical research design
[Source: Author's representation]

5.1 DEVELOPMENT OF RESEARCH HYPOTHESES

Since Beaver (1966) and Altman (1968), a significant body of theoretical and empirical research has developed on the prediction of corporate insolvency and the modeling of corporate default risk. The explanatory indicators used can be grouped into *accounting-based* and *market-based* predictors which include liquidity, solvency, profitability ratios as well as other indicators, such as industry grouping or the introduction of ESUG. According to du Jardin (2009), the prevailing approach to select exogenous variables in default prediction is based on their general popularity in the literature and their respective ability to predict payment defaults in previous studies. The literature review conducted in Chapter 4.1 mainly covers bankruptcy cases, company samples, and time periods based on U.S. data. In addition,

> "not much attention has been paid to industry effects in related academic literature so far. Following economic intuition, the inclusion of an industry grouping should improve discriminatory power and accuracy rates of fitted models. Divergent levels of competition among industries as well as different accounting conventions and regulatory requirements should impact the likelihood of insolvency cases. It is of particular interest to analyze if and to what extend industry variables improve discriminatory power and forecast accuracy of fitted models of accounting-based and market-based indicators [in Germany]" (Ledwon and Jäger, 2020, p. 58)

Figure 5.2 depicts the theoretical linkage to the relevant literature streams derived in Chapter 4.1 with respect to the categorization of used variables to promote the formulated theory-based hypotheses.[13]

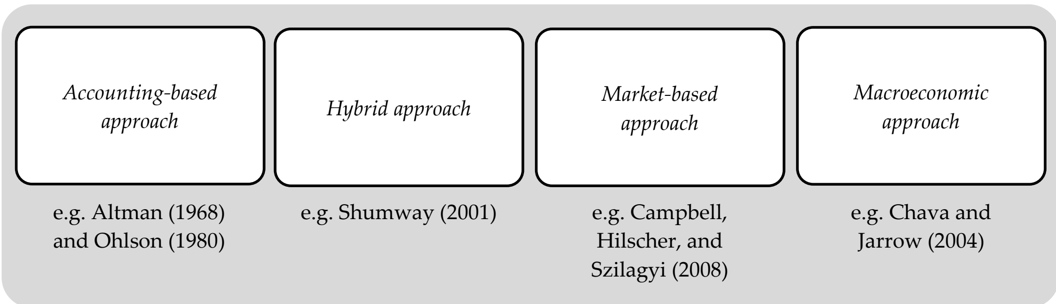

Figure 5.2: Linkage between relevant literature and theory-based hypotheses

[Source: Author's representation]

[13] Table 5.4 and Appendix A-4.3 cluster explanatory covariates by its source, category, and, if available, by the sign of its coefficient.

With regard to the methodologies applied, little attention has so far been paid to modeling the Cox proportional hazards regression to assess the default risk of non-financial German-listed companies represented in CDAX. Therefore, as a starting point, the following four hypotheses are formulated[14] to examine accounting and financial ratios as well as industry effects that are statistically significant in a semiparametric Cox proportional hazards model fit:[15]

$\boldsymbol{H_{1a}}$: *The market-based variable selection, proposed by Campbell, Hilscher, and Szilagyi (2008) in Model (3), shows a statistical improvement in terms of discriminatory power of fitted PD models compared to a hybrid approach proposed by Shumway (2001) in Model (2) and a parsimonious accounting-based approach based on covariates recommended by Altman (1968) and Ohlson (1980), among others, in Model (1).*

$\boldsymbol{H_{2a}}$: *The market-based variable selection, proposed by Campbell, Hilscher, and Szilagyi (2008) in Model (3) shows an improvement in terms of the accuracy rates of fitted PD models compared to a hybrid approach proposed by Shumway (2001) in Model (2) and a parsimonious accounting-based approach based on covariates recommended by Altman (1968) and Ohlson (1980), among others, in Model (1).*

$\boldsymbol{H_{3a}}$: *The inclusion of a categorial industry grouping according to the four-digit Standard Industrial Classification (SIC) improves the statistically discriminatory power of fitted PD models of accounting-based and market-based indicators in Models (1) – (4) IND.*

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[14] The formulated theory-based hypotheses are derived from the literature review presented in Chapter 4.1. However, how scientists develop hypotheses is according to Popper rather an intuitive process without following predefined rules and of minor importance as the primary objective should concentrate on hypotheses testing (Sedláček, 2012, p. 374; Schurz, 2013, pp. 27–28).

[15] Presented research hypotheses are derived from the research questions $\boldsymbol{RQ_1}$ to $\boldsymbol{RQ_4}$ presented in Chapter 1.2 and are formulated as alternative hypothesis $\boldsymbol{H_a}$. For the sake of simplicity, the null hypotheses are not listed separately.

***H*$_{4a}$:** *The inclusion of a categorial industry grouping according to the four-digit Standard Industrial Classification (SIC) improves forecasting accuracy of fitted PD models of the accounting-based and market-based indicators Models (1) – (4) IND.*

Empirical evidence on German default risk is scarce and is mostly rooted in variable selections, which are based on well-recognized U.S. literature as highlighted in Figure 5.2. Following the economic intuition, the implementation of a Cox proportional hazards regression based on three different sets of covariates should lead to robust findings, even if these have not been comprehensively investigated on German data. However, such results need not necessarily be generalized to non-financial entities in Germany. A modified examination of German PD models can thus provide further insights into German insolvency characteristics and predictability. This dissertation examines a tailor-made variable selection for the German market since the majority of the research is predominantly focused on U.S. literature.

With a view to selecting a suitable sample, "Mertens, Poddig and Fieberg (2018) test insolvencies in the period 1991-2015, whereas the earliest year for identifying insolvency … is set to the year 2000 since InsO entered into force in 1999" (Ledwon and Jäger, 2020, p. 58). The present dissertation, therefore, deals with the introduction of the first uniform insolvency statute in Germany. This approach is in line with the sample selection approach proposed by Hillegeist et al. (2004), which took into account statutory changes in the U.S. The underlying sample extends from 2000 to 2018. The selected time period can thus be seen as a long time horizon suitable for analyzing and testing low default rates (Sobehart, Keenan, and Stein, 2000, p. 8). However, the impact on the ESUG, which was implemented in 2012, should be taken into account as the empirical evidence is limited. The main objectives of the ESUG are twofold. First, the primary aim lies "in strengthening creditors' rights through earlier involvement and greater influence in the selection of the insolvency administrator" (Ledwon and Jäger, 2020, pp. 75). Second, the

> "ESUG creates incentives to apply for the opening of insolvency proceedings at an early stage in order to enhance the chances of successfully restructuring the company. Hence, self-administration has been strengthened, protective shield

proceedings introduced and the insolvency plan procedure streamlined" (Ledwon and Jäger, 2020, pp. 75–76).

According to the legal news provider JUVE (2018), ESUG procedural measures are mainly used by large companies. Between 2014 and 2017, half of the 200 largest corporate insolvencies were settled in self-administration and a third in protective shield proceedings. According to the law firm Buchalik and Brömmekamp (2018),

> "the ESUG created incentives for the early filing of an insolvency application. The sooner the application is made and the more cash the company has available, the greater are the chances of successful restructuring under insolvency protection. It may seem surprising, but by naming imminent insolvency as a reason for filing an insolvency application the legislature wanted to reward companies that decide to apply for insolvency early on. The legislature clearly intended for the new law to make insolvency a strategic option" (Buchalik Brömmekamp Rechtsanwaltsgesellschaft mbH, 2018, p. 12).

In a nutshell, the recent evaluation of the introduction of ESUG strengthened the restructuring culture in Germany (Madaus, 2017, p. 332) and companies should enter insolvency proceedings in a healthier state (Buchalik Brömmekamp Rechtsanwaltsgesellschaft mbH, 2018, p. 12). Translating this theoretical evaluation and observation into quantitative empirical research, one should observe declining hazard ratios in computed Cox's proportional hazards regression models after the legislative change. In summary, the following three hypotheses will be tested:

$\boldsymbol{H_{5a}}$: *The stepwise variable selection procedure for Cox's proportional hazards model with forward and backward iteration steps statistically improves the discriminatory power of the fitted PD models presented in Model (4) and Model (4) IND.*

$\boldsymbol{H_{6a}}$: *The stepwise variable selection procedure for Cox's proportional hazards model with forward and backward iterations steps improves accuracy rates of the fitted PD models presented in Model (4) and Model (4) IND.*

$\boldsymbol{H_{7a}}$: *Since the introduction of ESUG in 2012, a statistically significant decrease in hazard ratio with regard to fitted interaction should be observed. Companies that implement*

ESUG measures according to InsO Sections 270a and 270b should be associated with a healthier financial situation and therefore have a lower risk of filing for insolvency if all other covariates presented in Models (1) – (4) ESUG are kept constant.

5.2 DATA AND DESCRIPTIVE STATISTICS

In the third part of his publication *Important Characteristics, Weaknesses and Errors in German Equity Data from Thomson Reuters Datastream and their Implications for Empirical Studies on Stock Returns*, Brückner (2013) emphasizes that robust and valid empiric results require a high degree of data quality (Brückner, 2013, p. 8). Therefore, the formal requirement for conducting reliable empirical research depends on the availability of high-quality data. According to Ince and Porter (2006), the Thomson Reuters Datastream (TDS) plays an essential role in international finance as an increasing number of international, and German studies rely on its broad and deep coverage and can therefore be compared with the available data in Bloomberg (Ince and Porter, 2006, p. 463). However, naive use of TDS data can have an immense economic inference. Ince and Porter offer screening procedures to minimize erroneous data output (Brückner, 2013, p. 14). Therefore, relevant pitfalls proposed by Ince and Porter are introduced and extended to the specific needs of the research carried out. In addition, data adjustment measures, descriptive sample statistics summarizing the properties of the insolvency indicator introduced are presented, and an industry breakdown is provided. The Kaplan-Meier survival curve estimate, as well as the Nelson-Aalen estimator of the cumulative hazard based on the adjusted data sample, are used to analyze the data sample from a non-parametric perspective. Finally, for this dissertation, exogenous variables are selected, which were significant predictors of corporate default in previous empirical research.

5.2.1 Data adjustment

Raw data was collected by TDS. The extracted sample consists of 2,037 entries in total. As highlighted in Chapter 3.2, the InsO came into force in 1999, and therefore, the earliest year for determining insolvency was set at 2000. Thus, this dissertation follows the sample selection approach proposed by Hillegeist et al. (2004) which took into account the statutory changes in the U.S. Moreover, a long time horizon of more than ten years of data provides panel data large enough to analyze and test insolvencies (Sobehart, Keenan, and Stein, 2000, p. 8). Therefore, the raw sample compromises active and dead firms for the German equity market from 2000-2018. In this context, raw TDS data were screened on the basis of various characteristics and manually excluded. Following Fama and French (1992), only non-financial entities are included in the final sample, as the inclusion of financial entities may dilute the estimation results due to an overall high leverage that is industry-specific for the banking and financial services sector (Fama and French, 1992, p. 429). Thus, all financial firms were excluded on the basis of the well-known four-digit Standard Industrial Classification (SIC).[16] The next step is to perform data adjustment with regard to security type. In reference to the variable $NAME$, a distinction is made between security types to distinguish between preferred equity and common equity. Ince and Porter propose to search the name field for key phrases, create a candidate list of companies for exclusion by extracting all names containing those phrases, and review the list of observations for all companies that should not be removed from the sample. Combinations such as pf and $pref$ were examined, among other things, to identify preferred stock. Successive verification steps ensure that valid observations are not removed (Ince and Porter, 2006, p. 471).

The primary aim of this dissertation is to assess and improve the default risk of German-listed companies. The CDAX index comprises the shares of all domestic companies listed in the Prime and General Standard segments (Deutsche Börse Group, 2004, p. 5). The General Standard is defined as a segment that fulfills statutory requirements such as the publication of annual/semi-annual reports and ad-hoc disclosures in German, while the Prime Standard comprises those segments that meet the disclosure requirements of international standards (Deutsche Börse Group, 2004, p. 3). In summary, imitating the CDAX index covers the German equity market in its entirety, i.e. all companies listed on the Frankfurt

[16] SIC code 6000-6799 (Finance, Insurance and Real Estate)

Stock Exchange, and is therefore particularly suitable for research and analysis segments (Deutsche Börse Group, 2004, p. 5). Therefore, the initial sample was filtered in relation to the above-mentioned segments $SEGN$ and the $COUNTRY$ of origin in order to replicate the domestic German equity market. The variable $ACTIVITY$ as a TDS status indicator is used to classify a company as $DEAD$. In summary, 488[17] active German non-financial companies with equity listings on the *Deutsche Börse* in Frankfurt in the time period from 2000 to 2018 were examined. As a result,

> "the cleansed sample consists of 488 firms through 19 discrete time intervals leading to 6,622 firm observations. Through careful web searches, the delisting causes of 184 inactive firms have been identified. 97 insolvency proceedings according to InsO Sec. 17-19 have been reconstructed. Reasons for leaving the stock market are manifold. The remaining 87 inactive firms have left the stock market inter alia due to M&A activity, spin-off or squeeze out. All exits have been tracked with the exact date and respective source. In case of insolvencies, the date of opening based on ad-hoc announcements had to be manually retrieved. In order to foster transparency, all main court decisions are published and can be researched on the internet on the online record of the Ministry of Justice (Insolvenzordnung (InsO), 2018, Sec. 9). In practice, detailed information such as insolvency court in charge as well as detailed contact details is necessary in order to retrieve respective data. Consequently, data could not be gathered in all cases from the website: http://www.insolvenzbekanntmachungen.de. As a result, the website: http://www.dgap.de provides alternative input. In a few cases, press releases have been utilized to determine exits" (Ledwon and Jäger, 2020, p. 64).

In summary, it can be said that perfect data accuracy is rarely achieved. The required degree of data accuracy can vary considerably depending on the type of application (Brückner, 2013, p. 148). After successful data adjustment, the next step

[17] For sample size validation see inter alia Stiftung Familienunternehmen (Ed.) (2019), p. 17 with an adjusted sample for non-financial entities in CDAX with 487 constituents in 2018.

in the analysis of survival time should be a thorough univariate analysis (Hosmer, Lemeshow, and May, 2011, p. 9).

Table 5.1 contains descriptive sample statistics on the above insolvency indicator. The cumulative insolvency rate of the collected sample period was 19.88%. In particular, average annual insolvency rates vary between 0.00% and 3.81%, indicating that insolvencies are a relatively rare event among publicly traded German companies. Furthermore, the annual insolvency rates show fluctuation and correlation with the overall economic cycles. In particular, there are highs in 2002 during the abandoned *Neuer Markt* segment (3.81%), where many of the companies included in the survey voluntarily switched to the regulated market before filing for insolvency proceedings (Burghof and Hunger, 2003, p. 20). Furthermore, the table supports post-crisis effects related to the global financial crisis, which has affected insolvencies in 2009 (3.06%) and the Eurozone crisis in 2013 (3.05%).

Table 5.1: Total number of active companies and insolvency rate

This table contains sample descriptive statistics summarizing the characteristics of the insolvency indicator introduced.

Year	Active firms	Insolvency proceedings	Insolvency rate (%)
2000	346	0	0.00
2001	356	6	1.69
2002	341	13	3.81
2003	339	1	0.29
2004	340	6	1.76
2005	347	3	0.86
2006	372	2	0.54
2007	381	3	0.79
2008	377	6	1.59
2009	360	11	3.06
2010	350	10	2.86
2011	347	3	0.86
2012	343	3	0.87
2013	328	10	3.05
2014	306	3	0.98
2015	303	5	1.65
2016	298	5	1.68
2017	300	3	1.00
2018	304	4	1.32
Full Sample	**488**	**97**	**19.88**

[Source: Author's representation]

Next, descriptive sample statistics are provided to summarize the industry-specific characteristics related to the insolvency indicator. For this purpose, SIC codes are retrieved from the TDS as a uniform classification system. The industries in the sample are clustered into 8 divisions based on the 4-digit SIC code. Table 5.2. underpins industry-specific insolvency rates. Observations classified under SIC codes 1800-1999 are not taken into account. In addition, SIC codes 6000-6799 (Finance, Insurance, and Real Estate) were excluded in this dissertation as outlined above. The manufacturing sector dominates with more than half of the insolvencies (50.52%), followed by the service sector (31.96%).

Table 5.2: Sample statistics: Insolvencies sorted by SIC-Division

This table contains descriptive sample statistics summarizing the characteristics of the introduced insolvency indicator based on 4-digit SIC code.

SIC codes	SIC division	Insolvency proceedings	Insolvency rate (%)
0100-0999	Agriculture, forestry, and fishing	1	1.03
1000-1499	Mining	2	2.06
1500-1799	Construction	4	4.12
2000-3999	Manufacturing	49	50.52
4000-4999	Transportation, communications, electric, gas, and sanitary services	3	3.09
5000-5199	Wholesale trade	3	3.09
5200-5999	Retail trade	4	4.12
7000-8999	Services	31	31.96

[Source: Author's representation]

Retrieving the four-digit SIC code allows for more comprehensive data analysis, as shown in Table 5.3. Machinery and equipment (10 filings) and electronic and other electric equipment (13 filings) dominate with 10.31% or 13.40% of insolvency proceedings within the manufacturing division. As far as the SIC division services are concerned, the business service industry (21 filings) has a major influence on insolvency rates with 21.65% on a division level.

Table 5.3: Insolvencies sorted by SIC-Division and Industry

This table contains sample descriptive statistics summarizing the characteristics of the introduced insolvency indicator based on 4-digit SIC code at an industry level.

SIC codes	SIC division/ SIC industry	Insolvency proceedings	Insolvency rate (%)
0100-0999	**Agriculture, forestry, and fishing**	**1**	**1.03**
08	Forestry	1	1.03
1000-1499	**Mining**	**2**	**2.06**
10	Metal, mining	1	1.03
12	Coal mining	1	1.03
14	Nonmetallic minerals, except fuels	0	0.00
1500-1799	**Construction**	**4**	**4.12**
15	General building contractors	3	3.09
16	Heavy construction, except building	1	1.03
2000-3999	**Manufacturing**	**49**	**50.52**
22	Textile mill products	1	1.03
23	Apparel & other textile products	4	4.12
24	Lumber & wood products	1	1.03
26	Paper & allied products	4	4.12

SIC codes	SIC division/ SIC industry	Insolvency proceedings	Insolvency rate (%)
27	Printing & publishing	3	3.09
28	Chemical & allied products	4	4.12
30	Rubber & miscellaneous plastics products	2	2.06
32	Stone, clay, & glass products	1	1.03
33	Primary metal industries	3	3.09
34	Fabricated metal products	2	2.06
35	Industrial machinery & equipment	10	10.31
36	Electronic & other electric equipment	13	13.40
37	Transportation equipment	1	1.03
4000-4999	**Transportation, communications, electric, gas, and sanitary services**	**3**	**3.09**
45	Transportation by air	2	2.06
48	Communications	1	1.03
5000-5199	**Wholesale trade**	**3**	**3.09**
50	Wholesale trade – Durable goods	3	3.09
5200-5999	**Retail Trade**	**4**	**4.12**
52	Building materials & gardening supplies	1	1.03
56	Apparel & accessory stores	1	1.03
57	Furniture & home-furnishing stores	1	1.03
59	Miscellaneous retail	1	1.03
7000-8999	**Services**	**31**	**31.96**
73	Business services	21	21.65

SIC codes	SIC division/ SIC industry	Insolvency proceedings	Insolvency rate (%)
78	Motion pictures	5	5.15
79	Amusement & recreation services	1	1.03
87	Engineering & management services	4	4.12

[Source: Author's representation]

5.2.2 Non-parametric data analysis

One of the main objectives of this section is to apply the theoretically derived non-parametric data analysis in Section 4.3.1, namely the Kaplan-Meier survival curve estimation, as well as the Nelson-Aalen estimator of the cumulative hazard, based on the adjusted data sample. Corresponding non-parametric results form the basis for the subsequent Cox proportional hazard regression analysis, which is performed in Chapter 5.3 to investigate explanatory variables.

The non-parametric data analysis carried out takes into account 488 non-financial entities of the CDAX between 01.01.2000 and 31.12.2018. 97 of the sample have filed for insolvency during the observation period. Therefore, the adjusted data sample is divided into 19 discrete time intervals $[t_0; t_1]; [t_1; t_2]; \ldots; [t_{18}; t_{19}]$. Each company i entering the study at observation time t_0 is categorized as active. Consequently, companies that enter the German stock market after t_0 are also active firms. In terms of default, $y_{i,t}$ is binary for company i at time t, assuming only two values coded as one or zero. If the default is documented, a change of state, i.e. $y_{i,t}$ = 1, is only observed in the year of the respective default. So, the companies disappear in the year after the event. Likewise, a firm that survived until the last period t_{19} cannot have failed in earlier periods and therefore does not change its state from zero to one. In this way, the non-parametric analysis is adjusted for right-censored data. The average survival time of all 488 companies included in the study is 13.57 years. If one focuses on companies that file for insolvency (97 insolvencies) within the time under study, the average survival time is 8.22 years, while active companies that do not change their status and some of which disappear for reasons other than insolvency (another 87 exits) have an average survival time of 14.90 years. In particular, right-censored data, i.e. companies that survive until the last interval of the study, lead to an underestimation of the survival time for active companies. Next, the proposed estimators are presented by first introducing the Kaplan-Meier estimator and the consideration of right-censored data, as tabulated in Appendix A-5.1.

Figure 5.3 illustrates the relationship between survival probability and hazard rate by taking into account the first high initial hazard, thus describing the high mortality rate of observations in early life (Moore, 2016, p. 12). In other words, non-financial companies that are listed in CDAX and have a short survival period are more likely to file for insolvency proceedings without taking explanatory variables into account. The solid line represents the step function augmented with associated confidence intervals. In particular, a 95% confidence interval corresponding to an asymptotic variance is reported (Kalbfleisch and Prentice, 2002, p. 18). Horizontal solid lines represent the survival period in annual intervals terminated by the binary event variable insolvency. The height of the vertical lines indicates the change in cumulative survival probability. The tick marks represent censored observations that reduce the cumulative survival between intervals. Based on economic intuition, the graph confirms a stagnation of the hazard rate after a survival of more than 15 years, compared with the cumulative hazard rate of 15% within the first 10 years. As highlighted in Appendix A-5.2, the cumulation of events after 10 years accounts for 67 insolvencies, while 364 entities are at risk, and 77 of censorings are cumulative. In other words, companies that enter the study at inception and become more mature are less likely to file for insolvency without consideration of explanatory factors, as 30 insolvency cases are reported for companies with a survival period of more than 10 years.

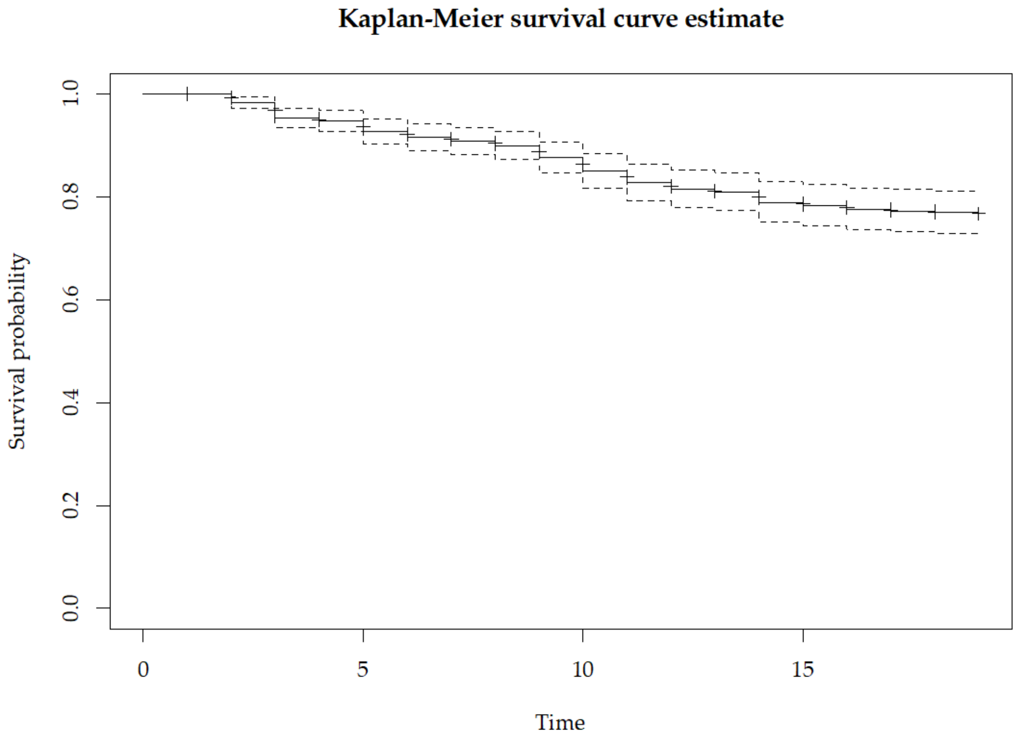

Figure 5.3: Estimation of the Kaplan-Meier survival curve
[Source: Author's representation]

In addition to the Kaplan-Meier estimator mentioned above, the Nelson-Aalen estimator is an alternative non-parametric estimator of the cumulative hazard rate function in the case of censored data or incomplete data, as introduced in Section 4.3.1. As a result, Figure 5.4 shows the results of the estimation of the cumulative hazard function using the Nelson-Aalen estimator. With regard to the objective of this dissertation, the Nelson-Aalen estimator describes the chances of an insolvency application within the scope of the study from a non-parametric perspective. As depicted in Figure 5.4, the Nelson-Aalen estimator again confirms the non-parametric economic intuition of the Kaplan-Meier estimator of a more likely probability of filing for insolvency if a company has a shorter survival time since reorganization or formation. Dotted lines represent the 95% probability that the confidence interval shown contains the true population means. Appendix A-

5.3 presents the estimator with supplementary data in accordance with the presentation of the Kaplan-Meier estimator mentioned above.

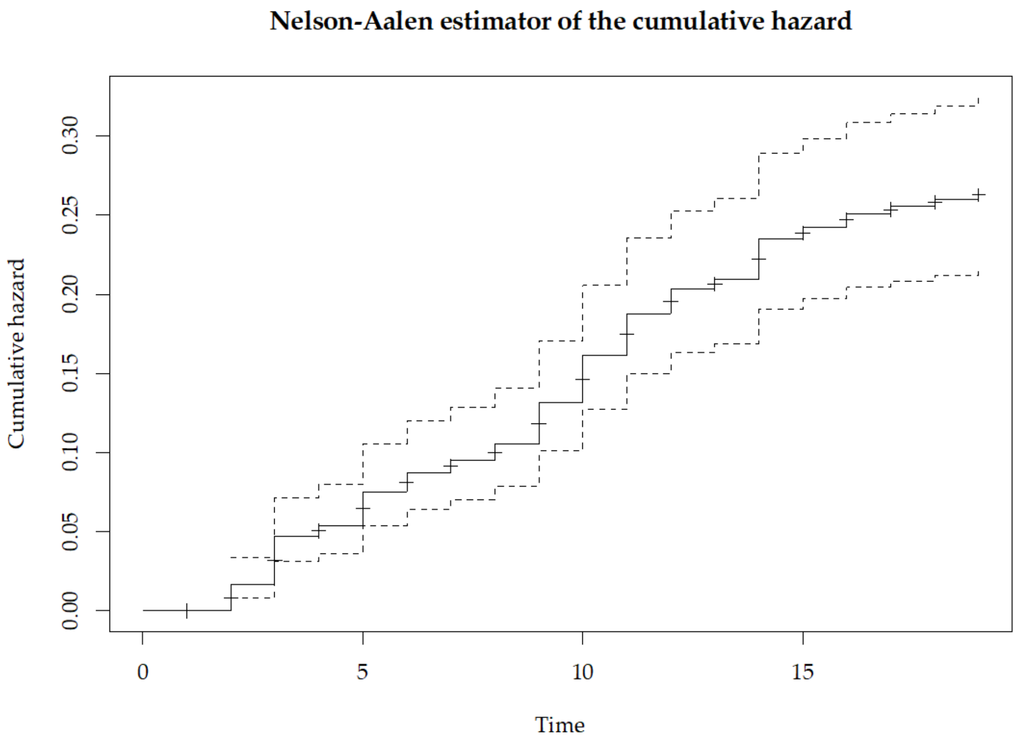

Figure 5.4: Nelson-Aalen cumulative hazard estimator
[Source: Author's representation]

This practical application of non-parametric descriptive analysis finalizes the descriptive data evaluation. Section 5.2.3 continues with the identification of used explanatory variables to be applied for the purpose of an advanced application of Cox proportional hazard regression analysis.

5.2.3 Selection of independent variables

This empirical part of this dissertation employs independent variables which were substantial predictors to assess the default risk in previous studies, as highlighted in Chapter 4.1 and summarized in Appendices A-4.1 to A-4.3. As a starting point, a comparative assessment of four enhanced Cox proportional hazards models will be applied. The variable selection ranges from accounting variables inspired by Altman (1968) and Ohlson (1980) to market-based variables proposed by Shumway (2001) and Campbell, Hilscher, and Szilagyi (2008), "based on a unique up-to-date database considering the inception of the InsO" (Ledwon and Jäger, 2020, p. 66). The variables used are divided into liquidity, solvency, profitability as well as other indicators. Furthermore, variables are clustered with respect to their data origin. A distinction is therefore made between accounting-based ratios, market-based indicators, and market-based predictors supplemented by macroeconomic information to analyze the theory-based hypotheses in depth. A total of 15 ratios were constructed using annual data from TDS.

The liquidity ratios presented by $CASHTA$ and $CASHMTA$ provide information on the ability of a company to meet its due obligations with a short-term orientation. As a starting point, a company's cash holdings are divided by its total assets to obtain a measure of short-term liquidity. If a company does not have a satisfactory cash balance and cannot refinance itself, this should predict probable insolvencies. The traditional method of measuring total assets is based on book value, but Campbell, Hilscher, and Szilagyi (2008) quantify the equity portion of total assets at market value by adding the book value of liabilities to the market value of equities, known as $CASHMTA$. The authors suggest that adjusted market-driven ratios allow more powerful predictions because market prices can contain novel information about the company's prospects more efficiently and accurately (Campbell, Hilscher, and Szilagyi, 2008, p. 2911). In summary, a more precise measure of a company's total assets can be obtained as market equity capitalization is observable in real-time and considers latest corporate events. In addition, it allows for the consideration of financing capacity either through the issuance of equity or the potential to secure short-term financing (Campbell, Hilscher, and Szilagyi, 2008, p. 2905).

Solvency measures contain three exogenous variables. A leverage ratio is added by calculating total liabilities relative to total assets, known as the $TLTA$. Once more, a market-driven ratio on the basis of this accounting version is presented, computed as total liabilities divided by the sum of market equity and book liabilities, called the $TLMTA$. The third market-driven variable introduced is the idiosyncratic standard deviation of stock returns of each company, referred to as $SIGMA$. According to Shumway (2001), $SIGMA$ is both empirically and rationally closely linked to insolvency since companies with high volatility in cash flows are more likely to be affected by insolvency proceedings. Consequently, $SIGMA$ metaphorizes the operating leverage (Shumway, 2001, p. 116). The "annualized standard deviation of the residual of a daily regression to its benchmark index CDAX" (Ledwon and Jäger, 2020, p. 66) is computed to construct $SIGMA$.

Net income divided by a company's total assets, referred to as $NITA$, is one of the profitability variables presented in the empirical part of this dissertation. This accounting-based predictor was augmented by its market-driven indicator, $NIMTA$. Furthermore, the past excess return, $EXRET$, is determined as the past excess return of a company "in year $t-1$ minus the value-weighted CDAX benchmark index return in year $t-1$" (Ledwon and Jäger, 2020, p. 66). The annual return of each company is assessed by cumulating monthly returns. If some of the monthly returns of a company are missing, the missing return is replaced by the value-weighted benchmark index return (Shumway, 2001, p. 115).

$$EXRET_{i,t} = log\left(1 + R_{i,t}\right) - log\left(1 + R_{CDAX,t}\right) \tag{5.1}$$

Equation 5.1: Past excess return
[Source: (Campbell, Hilscher, and Szilagyi, 2011, p. 18)

$EXRETAVG$ is computed as a stock excess return over the CDAX using geometrically decreasing weights and $\emptyset = 2^{-\frac{1}{3}}$, in accordance with the literature (Campbell, Hilscher, and Szilagyi, 2008, p. 2911).

$$EXRETAVG_{i,t} = 1\frac{1-\emptyset}{1-\emptyset^{12}}\left(EXRET_{t-1} + \dots + \emptyset^{11}\, x\, EXRETAVG_{t-12}\right) \tag{5.2}$$

Equation 5.2: Average past excess return
[Source: Campbell, Hilscher, and Szilagyi (2011, p. 19)

Finally, the relative size, represented by *RSIZE,* is measured as the natural logarithm of the market capitalization of each company at the end of the year preceding the year under observation in relation to the total size of the CDAX.

Additional exogenous variables examined in the models are $PRICE$, which tracks the trend of financially unstable firms trading at low stock quotes, the market-to-book ratio, MB, as an adjustment factor for market-driven variables used, and $YEAR$, as a continuous variable predictor for fluctuating insolvency rates in the survival study time. $PRICE$ is calculated as log price per share of the company at the end of the period and truncated above EUR 15. Following economic intuition, companies in distress have a propensity to develop low equity prices and thus a diminishing market capitalization. Previous research has argued that fluctuations above USD 15 do not appear to affect the probability of default so that the predictor variable is thus limited to above EUR 15 (Campbell, Hilscher, and Szilagyi, 2008, p. 2906). Next, MB concentrates on the relative value of a company's market capitalization in relation to the adjusted book value of equity ($BE_{adjusted}$). According to Campbell, Hilscher, and Szilagyi (2008), the book value of equity is modified by the difference between the market capitalization and the book value of equity to correct for incorrectly measured and overly large values of MB, as presented in Equation 5.3.

$$BE_{adjusted\ i,t} = BE_{i,t} + 0.1\left(ME_{i,t} – BE_{i,t}\right) \tag{5.3}$$

Equation 5.3: Adjusted book value of equity
[Source: Campbell, Hilscher, and Szilagyi (2011, p. 17)

Therefore, MB operates as an adjustment coefficient since the above predictors are all calculated on the basis of market value (Campbell, Hilscher, and Szilagyi, 2008, p. 2911). If the book value is significant, the probability of insolvency increases with MB (Campbell, Hilscher, and Szilagyi, 2008, p. 2911). $YEAR$ considers the different insolvency rates for the given period from 2000 to 2018 as continuous exogenous variable. Finally, the industry grouping, IND, according to the 4-digit SIC code, is utilized for the analysis of industry effects and the dichtomous variable $ESUG$ is introduced as interaction term. Table 5.4 summarizes the computed exogenous variables in this dissertation.

Table 5.4: Definition of exogenous variables and expected signs

In this table, the exogenous variables computed in this dissertation are presented, and a short description and expected coefficient regression signs derived from the literature review are given.

Variables	Category	Description	Exp. signs
Solvency			
$SIGMA$	*Market*	$SIGMA$ is calculated as the annualized standard deviation of the residual of a daily regression against the benchmark index CDAX.	+
$TLMTA$	*Market*	$\frac{total\ liabilites_{i,t}}{market\ capitalization_{i,t} + total\ liabilites}$	–
$TLTA$	*Accounting*	$\frac{total\ liabilites_{i,t}}{total\ assets_{i,t}}$	–
Liquidity			
$CASHMTA$	*Market*	$\frac{cash\ \&\ short - term\ investments_{i,t}}{market\ capitalization_{i,t} + total\ liabilites}$	–
$CASHTA$	*Accounting*	$\frac{cash\ \&\ short\ term\ investments_{i,t}}{total\ assets_{i,t}}$	–
Profitability			
$EXRET$	*Market*	$log(1 + R_{i,t}) - log(1 + R_{CDAX,t})$	–
$EXRETAVG$	*Market*	$\frac{1 - \emptyset}{1 - \emptyset^{12}}(EXRET_{t-1} + \cdots + \emptyset^{11}EXRETAVG_{t-12})$	–
$NIMTA$	*Market*	$\frac{EBITDA_{i,t}}{market\ capitalization_{i,t} + total\ liabilites}$	–
$NITA$	*Accounting*	$\frac{EBITDA_{i,t}}{total\ assets_{i,t}}$	–
$RSIZE$	*Market*	$log\left(\frac{market\ capitalization_{i,t}}{market\ capitalization_{CDAX,t}}\right)$	–

Variables	Category	Description	Exp. signs
Other variables			
$PRICE$	*Market*	$min[log(PRICE_{i,t}); log(15)]$	−
MB	*Market*	$\frac{market\ capitalization_{i,t}}{book\ value\ of\ equity_{adjusted,i,t}}$	+
$YEAR$	*Macro*	$YEAR$, accounts for the different insolvency rates for the given period as a continuous variable.	−
IND	*Macro*	The categorial grouping according to the four-digit SIC code is used to analyze industry effects.	+/−
$ESUG$	*Macro*	A dichotomous variable that takes the value 0 for company-year observations before the ESUG came into force and 1 after the inception of ESUG in 2012.	−

[Source: Author's representation]

5.3 EMPIRICAL RESULTS

Static logistic regression examines the existence or non-existence of an interest attribute (Rodríguez, 2007a, p. 1). However, static logistic regression does not provide information on how the existence or non-existence of an interest attribute is related to the intrinsic time effects of an explicit event (Rodríguez, 2007b, p. 1). Furthermore, censored observations are neglected, which means that for some companies, the event of insolvency has not happened at the time the data is analyzed. Lastly, the effect of independent predictors in relationship to its survival time is not considered, nor is it statistically evaluated (Rodríguez, 2007b, p. 1). Therefore, static logistic regression is inefficacious in evaluating insolvency predictors.

As described in Section 4.3.3, an extended version of the Cox regression model, allowing for AG-CP, forms the methodological basis for assessing the default risk of non-financial German-listed companies represented in CDAX and for testing the research hypotheses mentioned above. In particular, an application of a Cox proportional hazards regression model (Cox, 1972) includes

> "both a non-parametric aspect in the sense that it involves an unspecified function in the form of an arbitrary baseline hazard function, referred to as $h_0(t)$, and parametric model characteristics, as it allows modeling of the relationship between the failure rate and explanatory covariates" (Ledwon and Jäger, 2020, p. 61).

This type of methodology is therefore often referred to as a semiparametric model (Kalbfleisch and Prentice, 2002, p. 95).

5.3.1 Fitting Cox's proportional hazards regression model

In Section 4.3.3 and Chapter 4.4, a derivation of a suitable research method and basic concepts of survival analysis, in particular, an extended version of the semiparametric Cox proportional hazards regression analysis and a set of validation measures were theoretically investigated. Because time-independent variables for a given company do not change over time, the selected model design considers both time-independent and time-dependent variables, whose value changes over time. Therefore, an extended version of the Cox model is applied, allowing for the AG-CP. This dissertation adjusts the survival analysis with discrete time intervals to reflect the occurrence of defaults. (Hosmer, Lemeshow, and May, 2011, p. 17). Although insolvency dates were tracked as exact dates, annual data intervals were chosen on the following grounds. First, discrete yearly time intervals provide comparability of accounting, market-based, and macroeconomic indicators. Second, the approach allows comparability with default studies conducted by Shumway (2001), Chava and Jarrow (2004), Campbell, Hilscher, and Szilagyi (2008) and Mertens, Poddig, and Fieberg (2018).

Therefore, the estimate of the survival function is based on 19 consecutive yearly intervals, which are denoted as $[t_0; t_1]; [t_1; t_2]; \dots; [t_{18}; t_{19}]$. Each company i entering the study at observation time t_0 is categorized as active. Andersen-Gill counting process (AG-CP) is used as time progresses. This means that the start/stop intervals for each company-year observation is considered. Since companies have multiple observations in the data setup, fitted models take into account the correlation within each company by using a cluster variance represented by the argument $cluster\ (IDENT)$. The event variable of interest is based on the following assumptions.

> "The event variable default $y_{i,t}$ is binary for firm i at time t assuming only two values coded as one and zero. If insolvency according to InsO Sec. 17-19 is documented, a change of state occurs, i.e. $y_{i,t} = 1$, and the firm disappears from the sample in the year following the event. In addition, firms are removed from the study without filing for insolvency inter alia due to M&A activity, spin-off, or squeeze-out. Likewise, a firm that survives to the last period t_{19} cannot have failed in previous periods and thus does not change its state from zero to one. This universal characteristic of survival data is known as right-censoring" (Ledwon and Jäger, 2020, p. 61).

Accounting data used are lagged because the calendar years were selected. In a few cases, accounting information from the year before the insolvency are not available and are therefore replaced by the accounting data of the previous year. This adjustment seeks to simulate that accounting information is public to the market at the time of estimation (Chava and Jarrow, 2004, p. 543). In addition, this dissertation uses the Breslow method[18] to estimate the cumulative baseline hazard rate.

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[18] Since most statistical software uses the Breslow method by default, it was chosen as the default in this dissertation. The Efron approximation was tested and showed similar results in terms of exp(coef) and p-values. Therefore, no separate illustration is provided. Finally, the exact method was not considered due to the high computational effort involved.

5.3.2 Application of stepwise variable selection

After defining the assumptions and specifications of the Cox proportional hazards regression analysis, the next step is to present an iteration approach to obtain the best model fit to the given data. One major objective of regression analysis is to find a parsimonious regression approach that provides superior estimation results based on the pool of observed covariates (Hosmer, Jovanovic and Lemeshow, 1989, p. 1265). According to Zhang (2016b), "purposeful selection is performed partly by software and partly by hand, the stepwise and best subset approaches are automatically performed by software" (Zhang, 2016b, p. 1).

In general, automated algorithms do not fully take into account all characteristics of a data sample and the associated subject (Smith, 2018, p. 5). For this reason, the tailor-made model is thoroughly investigated with regard to out-of-sample discrimination, validation, and other GOF tests. However, the list of variables presented in Table 5.4 is the starting point for optimization in this empirical study, which is based on the comprehensive literature research provided in Chapter 4.1. Hence, the main objective of this section is to present a tailor-made model adaptation. As a model-fitting technique, the stepwise variable selection procedure is chosen in this dissertation to obtain the best candidate final regression model.

In particular, forward and backward iterations of significant and non-significant covariates and their moderators are applied. A significance level for entry (SLE) of 0.15 is chosen to reflect a conservative variable selection approach. The same p-value applies to the significance level for the stay (SLS) of 0.15. The best candidate model is automatically generated based on a list of covariates and moderators. To avoid multicollinearity, the selected threshold value of variance inflating factor (VIF) is taken into account. As a general rule for the interpretation of VIF, this empirical analysis considers a VIF greater than 10 for continuous variables and greater than 2.5 for categorical variables as an indication of an existing problem of multicollinearity. Table 5.5 shows the output of the final variable selection and the corresponding VIF analysis, which does not indicate a problem of multicollinearity.

Table 5.5: Variance inflating factor (VIF) analysis

This table presents the final explanatory variable selection based on VIF analysis and accounting for multicollinearity.

Stepwise final variable selection	Variance inflating factor (VIF)
YEAR	1.27
EXRET	1.49
PRICE	2.53
MB	1.01
SIGMA	2.20
EXRETAVG	1.31
TLMTA	2.74
NIMTA	2.44
CASHTA	1.81
CASHMTA	2.19

Note: Stepwise Final Variable Selection: in.lr.test: SLE = 0.15; out.lr.test: SLS = 0.15; limited variable selection in VIF = 2.50 (categorial)/10.00 (continuous). All results are based on the entire sample. [Source: Author's representation]

5.3.3 In-sample regression results

Before empirical in-sample results are presented, a brief discussion of the selection and economic intuition of the exogenous covariates within the Cox regression models used is examined. In the first column, Model (1) is inspired by Altman (1968) and Ohlson (1980). In the second column, Model (2) follows Shumway (2001) and estimates a model that includes six variables: $NITA$, $TLTA$, $EXRET$, $SIGMA$, $RSIZE$, and $YEAR$. Therefore, Model (2) considers assets in the traditional manner using book values. In Column 3, referred to as Model (3), the approach of Campbell, Hilscher, and Szilagyi (2008) is applied, enhancing book values with market-driven information, as explained in Section 5.2.3 and adding $CASHMTA$, $EXRETAVG$, $PRICE$, and MB, accordingly. Finally, in Column 4, represented by Model (4), the output of the stepwise variable selection procedure to obtain the best candidate final regression model is applied.

The following sections will more closely explore the empirical in-sample model results. Starting with the variable selection in Model (1), it

> "confirms the economic intuition and negative expected coefficient sign for $TLTA$ and $CASHTA$, which enter statistically significant at the level of 0.01. Holding the other covariates constant, one unit increase in $TLTA$ increases the hazard by a factor of 1.03, or 3%. In contrast to this minor effect, $CASHTA$ concludes a lower risk of insolvency with a provided hazard ratio of 0.08. Finally, $YEAR$ concludes an increasing insolvency risk of 6% per annum for the given survival study time at the statistical level of 0.05" (Ledwon and Jäger, 2020, p. 68).

In the second column of Table 5.6, the variables, proposed by Shumway (2001), form a set of pure accounting ratios and market-driven information.

> "All variables for Model (2) enter with expected signs, however in comparison to Model (1) the importance of market data is distinctly emphasized as all accounting variables enter insignificantly. $EXRET$ provides evidence that a firm's past excess return is a strong insolvency predictor. $SIGMA$ is strongly related to bankruptcy, both statistically and logically, as firms with a high volatility of returns are more likely to be affected by the event of filing for insolvency. $RSIZE$ proofs that increasing company size relative to the benchmark index reduces the risk of filing for insolvency. Model (2) underpins that with an increase in $YEAR$, constituents are less likely to be affected by insolvencies" (Ledwon and Jäger, 2020, p. 68).

Following the approach suggested by Campbell, Hilscher, and Szilagyi (2008),

> "Model (3) reconfirms the findings of Model (2) and underpins the statistical benefit of substituting accounting-based ratios by adjusted market-driven ratios. In addition, Model (2) and (3) show unambiguously the importance of past excess returns ($EXRET$ and $EXRETAVG$) and volatility ($SIGMA$). Furthermore, the price ($PRICE$) as well as the relation between book value of equity and market

capitalization (MB) play an essential role in default prediction as all aforementioned variables enter highly statistically significant" (Ledwon and Jäger, 2020, p. 68).

Model (4) represents the model output of the stepwise variable selection procedure to obtain the best candidate final regression model. The majority of variables occur with expected signs, but the positive hazard ratio of $CASHMTA$ is counter-intuitive. A limited interpretation of this covariate can be arrived at by looking more closely at their wide range of lower 0.95 and upper 0.95 confidence intervals. In addition, the algorithm does not include $RSIZE$ in the final variable selection, which is in line with the statistical insignificance of this variable in Model (3) and therefore does not show any correlation that an increase in the size of a company relative to the benchmark index reduces the risk of filing for insolvency. In addition, Model (4) includes the standard past excess returns of $EXRET$ and geometrically decreasing weights of $EXRETAVG$ relative to the CDAX in the stepwise variable selection procedure, thus confirming that past excess returns are of great importance for the prediction of insolvencies. Besides $SIGMA$, $TLMTA$ was chosen as the second measure of solvency, even though it is not statistically significant. This assumes a relationship to one of the other covariates included. Finally, for the given survival study period at the statistical level of 0.01, $YEAR$ arrives at a decreasing insolvency risk of 15% per annum and therefore supports the inclusion of the categorial variable in Models (2) and (3). The results are shown in Table 5.6.

Table 5.6: In-sample results for the entire sample without industry grouping

This table shows empirical in-sample results of the fitted PD Models (1) – (4) without industry grouping. The applied Cox proportional-hazards regression models are fitted using the statistical programming language R, taking into account AG-CP, as well as a cluster variance represented by the argument $cluster(IDENT)$, which accounts for the correlation within each firm. In addition, the results presented apply Breslow's method for estimating the cumulative baseline hazard rate. The presented standard errors are robust.

Exogenous variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
NITA	0.98 (0.94-1.02)	0.98 (0.93-1.03)		
NIMTA			0.87*** (0.82-0.92)	0.85** (0.78-0.93)
TLTA	1.03*** (1.01-1.05)	1.00 (0.97-1.02)		
TLMTA			1.51*** (1.15-1.98)	0.89 (0.66-1.15)
CASHTA	0.08*** (0.01-0.44)			0.05*** (0.01-0.30)
CASHMTA			0.80 (0.46-1.37)	2.42*** (1.56-3.74)
EXRET		0.23*** (0.18-0.30)		0.27*** (0.21-0.36)
EXRETAVG			0.00*** (0.00-0.00)	0.00*** (0.00-0.11)
SIGMA		1.93*** (1.50-2.49)	1.72*** (1.29-2.30)	1.59*** (1.18-2.14)
RSIZE		0.52*** (0.39-0.70)	0.87 (0.61-1.24)	
PRICE			0.44*** (0.25-0.77)	0.38*** (0.25-0.59)

Exogenous variables	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
MB			1.00*** (1.00-1.00)	1.00*** (1.00-1.00)
$YEAR$	1.06** (1.01-1.13)	0.85*** (0.76-0.95)	0.96 (0.89-1.04)	0.85*** (0.77-0.94)
n	6,622	6,622	6,622	6,622
Number of events	97	97	97	97
$Concordance$	0.64 se = 0.03	0.97 se = 0.01	0.97 se = 0.01	0.98 se = 0.01
Likelihood ratio test	20.35***	434.00***	387.90***	478.30***
Wald test	53.75***	554.30***	509.60***	621.00***
Score (log-rank) test	24.26***	1,643.00***	1,339.00***	1,709.00***
Schoenfeld global test	0.22	0.30	0.44	0.76

Note: exp(coef) are displayed for each variable. *** p<0.01, ** p<0.05, * p<0.1. All results are based on the entire sample. The lower .95 and upper .95 confidence intervals are given in parentheses. [Source: Author's representation]

Subsequently, in-sample empirical results with categorial industry grouping according to SIC-Division are presented. First, no changes in the coefficients of the previous variables are observed, which makes it possible to test the impact on industry. In contrast to Chava and Jarrow (2004), the empirical in-sample results suggest that German insolvency prediction is only influenced by the industry to which the company belongs since only a few of the IND variables have proven to be significant, apart from Model (1). In Model (2), it can be observed that $IND(2000-3999)$, $IND(4000-4999)$, and $IND(5000-5199)$ become statistically significant at a level of 0.05. The services sector represented by $IND(7000-8999)$ is statistically significant at the level of 0.01. Looking at the industry variables of Model (3), only the IND $(1500-1799)$ is statistically significant at 0.1. Finally, the stepwise variable selection method described in Model (4) confirms the statistical significance of IND $(4000-4999)$, IND $(5000-5199)$, and IND $(7000-8999)$.

As an in-sample GOF measure, "the concordance statistic for Cox models … is now the most used measure of goodness-of-fit in survival models" (Therneau and Atkinson, 2020, p. 1) and is used in this dissertation as a first approach to capture discriminatory power based on the entire sample before out-of-sample tests are performed. As was pointed out in Section 4.4.2, the interpretation of concordance is based on counting correct and incorrect predictions, also termed concordant and discordant (Therneau and Atkinson, 2020, p. 1). Focusing on the reported values of concordance, only minor improvements can be reported for Models (1) and (2), while Model (3) shows no change when the industry grouping is added. A look at Model (4) leads to the conclusion that concordance has not improved. However, Blanche, Kattan, and Gerds (2019) point out mathematically and derive examples that the concordance can be easily incorrectly specified for the time until event outcome, and therefore, the authors suggest that analysts use the state-of-the-art time-dependent AUC instead (Blanche, Kattan, and Gerds, 2019, p. 355). Therefore, in Section 5.4.2 for right-censored data, a time-dependent out-of-sample AUC is performed to comprehensively assess the discriminatory power of fitted models.

Table 5.7: In-sample results on entire sample with industry grouping

This table shows the empirical in-sample results of fitted PD Models (1) – (4) with industry grouping. The applied Cox proportional-hazards regression models are fitted using the statistical programming language R, taking into account AG-CP, as well as a cluster variance represented by the argument $cluster(IDENT)$, which accounts for the correlation within each company. In addition, the results presented apply Breslow's method for estimating the cumulative baseline hazard rate. The presented standard errors are robust.

Exogenous variables	**Model (1)** $\boldsymbol{IND}$	**Model (2)** $\boldsymbol{IND}$	**Model (3)** $\boldsymbol{IND}$	**Model (4)** $\boldsymbol{IND}$
$NITA$	0.99 (0.96-1.02)	0.98 (0.94-1.02)		
$NIMTA$			0.90** (0.81-0.99)	0.89** (0.81-0.98)
$TLTA$	1.04*** (1.02-1.05)	0.99 (0.97-1.02)		
$TLMTA$			1.56*** (1.20-2.04)	0.91 (0.71-1.17)
$CASHTA$	0.06*** (0.01-0.37)			0.06*** (0.01-0.31)
$CASHMTA$			0.94 (0.57-1.55)	2.79*** (1.78-4.37)
$EXRET$		0.24*** (0.19-0.31)		0.28*** (0.21-0.37)
$EXRETAVG$			0.00*** (0.00-0.00)	0.00*** (0.00-0.07)
$SIGMA$		1.98*** (1.54-2.56)	1.69*** (1.22-2.33)	1.67*** (1.24-2.25)
$RSIZE$		0.47*** (0.34-0.65)	0.82 (0.57-1.17)	
$PRICE$			0.41*** (0.24-0.68)	0.35*** (0.23-0.54)

Exogenous variables	**Model (1)** $\boldsymbol{IND}$	**Model (2)** $\boldsymbol{IND}$	**Model (3)** $\boldsymbol{IND}$	**Model (4)** $\boldsymbol{IND}$
MB			1.00*** (1.00-1.00)	1.00*** (1.00-1.00)
YEAR	1.07** (1.01-1.13)	0.82*** (0.74-0.92)	0.92* (0.84-1.01)	0.81*** (0.72-0.90)
IND (1000-1499)	1.93 (0.31-11.95)	1.80 (0.40-7.99)	2.80 (0.47-16.70)	1.64 (0.40-6.75)
IND (1500-1799)	1.21 (0.20-7.54)	0.60 (0.17-2.12)	2.98* (0.87-10.19)	0.95 (0.29-3.13)
IND (2000-3999)	0.62 (1.01-1.13)	0.25** (0.08-0.81)	1.17 (0.40-3.44)	0.42 (0.14-1.23)
IND (4000-4999)	0.24 (0.04-1.63)	0.13** (0.02-0.89)	0.36 (0.06-2.22)	0.20* (0.04-1.11)
IND (5000-5199)	0.62 (0.09-4.49)	0.21** (0.05-0.88)	0.69 (0.19-2.53)	0.31* (0.09-1.09)
IND (5200-5999)	0.76 (0.12-4.68)	0.69 (0.19-2.46)	2.21 (0.62-7.79)	0.81 (0.27-2.42)
IND (7000-8999)	0.83 (0.17-4.07)	0.17*** (0.05-0.59)	0.58 (0.19-1.76)	0.24** (0.07-0.76)
n	6,622	6,622	6,622	6,622
Number of events	97	97	97	97
Concordance	0.66 se = 0.03	0.98 se = 0.01	0.97 se = 0.01	0.98 se = 0.01
Likelihood ratio test	29.40***	448.00***	404.90***	490.70***
Wald test	72.90***	579.70***	575.60***	651.90***
Score (log-rank) test	34.64***	1,651.00***	1,361.00***	1,728.00***
Schoenfeld global test	0.36	0.81	0.34	0.99

Note: exp(coef) are presented for each variable. *** p<0.01, ** p<0.05, * p<0.1. All results are based on the entire sample. The lower .95 and upper .95 confidence intervals are given in parentheses. [Source: Author's representation]

The proportional hazards (PH) assumption is verified by evaluating the scaled Schoenfeld residuals global test and respective graphical diagnostics (Zhang et al., 2018, pp. 5–7) to be described in Section 5.4.1. Results of Schoenfeld's global test suggest that there is no violation of the PH assumption for presented models with respective p-values of 0.22 and 0.36 for Model (1), 0.30 and 0.81 for Model (2), 0.44 and 0.34 for Model (3), and 0.76 and 0.99 for Model (4). The graphical diagnostics of dfbeta, dfbetas, deviance, and Martingale residuals do not show serious influence observations or outliers as well as nonlinearity for fitted Model (2), Model (3) as well as Model (4). Once again, the weak discriminatory power of Model (1) is reassured by a violation of influential observations or outliers. Finally, the GOF of the fitted models is evaluated by the likelihood ratio test, Wald test, and score (log-rank) test. The aforementioned three statistics may be described as asymptotically equivalent (Fox and Weisberg, 2018b, p. 6). The statistical significance in Model (2), Model (3), and Model (4) shows significant improvement over the null point. Overall, the respective results represent robust empirical evidence to explain corporate insolvencies for German non-financial firms.

Finally, in-sample empirical results with interaction terms corresponding to the inception of ESUG are presented. The aim of this dissertation is therefore to investigate the effects of the ESUG implemented in 2012 on explanatory covariates, as empirical evidence on this legislative change is scarce. As described in Chapter 3.2, the ESUG aims to strengthen the rights of creditors by involving them earlier and giving them more power in selecting the insolvency administrator, and establishes incentives to file for the opening of insolvency proceedings at a preliminary phase to improve the likelihood of effectively restructuring the company (Moraht and Lütcke, 2012). According to legal news provider JUVE (2018), ESUG measures are mainly applied by large companies. Between 2014 and 2017, half of the 200 largest corporate insolvencies were settled in self-administration and a third in protective shield proceedings. Of the 97 insolvencies in this dissertation, 33 cases fall under this legislative regime. Of these 33 insolvencies, only 12 companies could be verified having taken measures in accordance with InsO Sections 270a and 270b. Prominent examples such as Air

Berlin, Beate Uhse, Loewe, or Pfleiderer, among others, represented filings in accordance with InsO Sections 270a and 270b. Consequently, the introduction of the ESUG should result in companies entering insolvency proceedings being in a healthier state. As a result, companies under the ESUG regime should be associated with a lower hazard rate. The following section examines the interaction between the inception of ESUG and the determinants of corporate insolvency. According to Scheike (2020), the terminology statistical interaction can be described as "an effect modification: the hazard ratio of one variable depends on the value of another variable" (Scheike, 2020, p. 27).

Model (1) $ESUG$ again confirms the economic intuition and negative expected coefficient sign for $CASHTA$, which becomes statistically significant at the level of 0.01. All other variables except the interaction terms become statistically insignificant. The interaction term $ESUG{:}\,CASHTA$ will not be discussed further due to its broad spectrum of confidence intervals. Most variables for Model (2) $ESUG$ are received with expected signs and magnitude. If one interprets the interaction term $ESUG{:}\,NITA$, one can conclude that one keeps the other covariates constant, one unit increase of the interaction term $ESUG{:}\,NITA$ reduces the hazard by a factor of 0.92 or 8% after the inception of ESUG in 2012. On the basis of this finding, it can be assumed that a decline in the hazard ratio is apparent compared with the basic Model (2). The interaction terms $ESUG{:}\,EXRET$ and $ESUG{:}\,SIGMA$, although becoming statistically significant, indicate counter-intuitive hazard ratios. According to Campbell, Hilscher, and Szilagyi (2008), Model (3) $ESUG$ and the stepwise variable selection in Model (4) $ESUG$ confirm the findings of Model (2) $ESUG$ and underpin the reduction in hazard rates in the interaction term $ESUG{:}\,NIMTA$ becoming statistically significant only for Model (4) $ESUG$ at the 1% level. The other interaction terms provide counter-intuitive results or cannot be further commented on due to a wide range of confidence intervals. Furthermore, all models except Model (4) $ESUG$ violate the PH assumption. Since global tests indicate a violation of PH assumption, no individual tests for each covariate and visual confirmation are performed in the following chapters. In particular, the low proportion of verified insolvency cases under ESUG does not provide robust and valid results to continue model discrimination and validation techniques. In summary, only for the interaction term in relation to $ESUG\colon NITA$ and $ESUG\colon NIMTA$ can one conclude decreasing hazard rates.

Table 5.8: In-sample results on entire sample with ESUG interaction term

This table shows empirical in-sample results of the fitted PD Models (1) – (4) with $ESUG$ interaction term. The applied Cox proportional-hazards regression models are fitted using the statistical programming language R, taking into account AG-CP, as well as a cluster variance represented by the argument $cluster(IDENT)$, which accounts for the correlation within each firm. In addition, the results presented apply Breslow's method for estimating the cumulative baseline hazard rate. The presented standard errors are robust.

Exogenous variables	**Model (1)** $\boldsymbol{ESUG}$	**Model (2)** $\boldsymbol{ESUG}$	**Model (3)** $\boldsymbol{ESUG}$	**Model (4)** $\boldsymbol{ESUG}$
$NITA$	0.97 (0.90-1.05)	1.04*** (1.02-1.07)		
$NIMTA$			0.89 (0.74-1.06)	1.11 (0.85-1.45)
$TLTA$	1.01 (0.96-1.07)	0.77 (0.55-1.07)		
$TLMTA$			1.13 (0.91-1.41)	0.67*** (0.54-0.83)
$CASHTA$	0.01*** (0.00-0.13)			0.04** (0.00-0.53)
$CASHMTA$			0.31 (0.06-1.52)	2.12 (0.45-10.01)
$EXRET$		0.19*** (0.13-0.27)		0.21*** (0.14-0.30)
$EXRETAVG$			0.00*** (0.00-0.01)	0.02** (0.00-0.67)
$SIGMA$		3.38*** (2.27-5.03)	4.40*** (2.77-7.00)	3.48*** (2.25-5.40)
$RSIZE$		0.70* (0.49-1.01)	0.82 (0.54-1.26)	

Exogenous variables	**Model (1)** ***ESUG***	**Model (2)** ***ESUG***	**Model (3)** ***ESUG***	**Model (4)** ***ESUG***
PRICE			0.82 (0.44-1.53)	0.69 (0.41-1.17)
MB			0.99** (0.98-1.00)	1.00 (0.98-1.01)
ESUG	1.16 (0.37-3.60)	0.62 (0.04-9.85)	0.65 (0.02-19.72)	0.16 (0.01-3.17)
YEAR	1.00 (0.91-1.10)	0.85 (0.76-0.95)	0.87** (0.76-1.00)	0.90 (0.78-1.03)
ESUG:NITA	0.98 (0.90-1.06)	0.92*** (0.88-0.96)		
ESUG:NIMTA			0.85 (0.69-1.05)	0.67*** (0.49-0.91)
ESUG:TLTA	1.02 (0.96-1.08)	1.30 (0.94-1.81)		
ESUG:TLMTA			108.93*** (6.47-1,833.93)	129.06*** (7.01-2,377.52)
ESUG:CASHTA	101.46*** (3.14-3,274.08)			20.63* (0.71-603.44)
ESUG:CASHMTA			2.67 (0.51-13.89)	0.53 (0.11-2.62)
ESUG:EXRET		1.96*** (1.30-2.95)		2.20*** (1.46-3.32)
ESUG:EXRETAVG			0.02 (0.00-23.09)	0.01 (0.00-22.24)
ESUG:SIGMA		0.41*** (0.24-0.69)	0.36*** (0.20-0.66)	0.41*** (0.24-0.71)

Exogenous variables	**Model (1)** $ESUG$	**Model (2)** $ESUG$	**Model (3)** $ESUG$	**Model (4)** $ESUG$
ESUG:RSIZE		0.58* (0.33-1.01)	1.11 (0.57-2.16)	
ESUG:PRICE			1.13 (0.42-3.05)	1.15 (0.41-3.19)
ESUG:MB			1.01** (1.00-1.02)	1.00 (0.99-1.02)
n	6,622	6,622	6,622	6,622
Number of events	97	97	97	97
$Concordance$	0.68 se = 0.03	0.98 se = 0.01	0.97 se = 0.01	0.97 se = 0.01
Likelihood ratio test	32.29***	464.30***	425.60***	512.90***
Wald test	132.90***	671.70***	808.40***	839.40***
Score (log-rank) test	41.11***	1,657.00***	1,377.00***	1,742.00***
Schoenfeld global test	0.00	0.00	0.04	0.66

Note: exp(coef) are presented for each variable. *** p<0.01, ** p<0.05, * p<0.1. All results are based on the entire sample. Lower .95 and upper .95 confidence intervals are given in parentheses. [Source: Author's representation]

5.4 GOODNESS-OF-FIT MEASURES AND OUT-OF-SAMPLE VALIDATION

Model diagnostic measures are carried out to determine whether the fitted Cox regression models in this dissertation adequately describe the results presented (Fox and Weisberg, 2018a, Chap. 8). Therefore, the proportional hazards (PH) assumption, influential observations, or outliers, as well as nonlinearity, are investigated. For this purpose, three main types of residuals are examined mainly graphically to verify the above model assumptions. First, scaled Schoenfeld residuals are performed and plotted to check the PH assumption, followed by deviance residuals to evaluate influential observations and outliers, and finally Martingale residuals to detect nonlinearity.

Model discrimination is assessed through GOF measures, with a focus on the time-dependent AUC ratio. It is important to note that the estimated AUC ratio in this dissertation is adjusted for time-dependency and censoring since both aspects influence the estimation results of the survival curves and the coefficients of survival regression analysis (Chambless and Diao, 2006, p. 1). The current German PD literature, inter alia represented by Elsas and Mielert (2010) and Mertens, Poddig, and Fieberg (2018), seems to use the standard approach of the AUC curve, and therefore a time-dependent approach aims to provide more accurate results.

A well-calibrated default risk model aims to predict defaults for German non-financial listed companies in the CDAX. According to Demler, Paynter, and Cook (2015), calibration is essential for the assessment of model performance, as calibrated models provide more accurate risk estimates and lead to appropriate decision making (Demler, Paynter, and Cook, 2015, p. 1). Therefore, a decile ranking is applied in Section 5.4.3. A well-calibrated PD model should provide high accuracy rates (AR) in the top deciles. The chosen approach of model calibration underpins the ability to clearly predict insolvencies of German non-financial companies represented in CDAX.

Table 5.9 provides an overview of model fitting criteria applied, the acceptable level, and interpretation. Panel 1 emphasizes the criteria of model diagnostics, while Panel 2 focuses on the evaluation of model discrimination, and Panel 3 shows criteria for model calibration.

Table 5.9: Model fit criteria and acceptable fit interpretation

This table presents appropriate model fitting criteria, acceptance level, and interpretation, divided into (A) model diagnostics, (B) model discrimination, and (C) model calibration.

Model fit criterion	Acceptable level	Interpretation
Panel A: Model diagnostics and fit		
Schoenfeld global test	$p > 0.10$	A global test indicates no violation of PH assumption; individual tests for each covariate and visual confirmation are recommended.
Deviance residuals	$Y = 0$	Detecting influential observations or outliers
Martingale residuals	$Y = 0$	Examining nonlinearity
Likelihood ratio test	$p < 0.05$	The *Likelihood ratio test*, *Wald test*, and *Score (log-rank)* test are statistics that are asymptotically equivalent. According to Hosmer, Lemeshow, and May (2011), "in situations where there is disagreement, … the likelihood ratio test is the preferred test" (Hosmer, Lemeshow, and May, 2011, p. 79).
Wald test	$p < 0.05$	
Score (log-rank) test	$p < 0.05$	
Panel B: Model discrimination		
Concordance	0.5 (random fit) to 1 (perfect fit)	Compares values in alternative models
iauc	0.5 (random fit) to 1 (perfect fit)	Compares values in alternative models
Wilcoxon rank-sum test	$p < 0.05$	Compares two *iauc* at specific times.
Panel C: Model calibration		
Walk-forward analysis and decile ranking	Accuracy rate (AR) in > 75% in top decile	Highest AR in decile 1, lowest in decile 10; based on the result set; no jumps or flat ARs, as it indicates incorrect calibration.

[Source: Author's representation]

5.4.1 Testing model assumptions

As introduced theoretically in Section 4.4.1, model diagnostics facilitate to determine whether the fitted Cox regression models in this dissertation appropriately describe the depicted results (Fox and Weisberg, 2018a, Chap. 8). Thus, the proportional hazards (PH) assumption, influential observations, or outliers, as well as nonlinearity, are investigated by applying the Schoenfeld (1982) global test at the covariate level, and a series of graphical visualizations to assess the above model assumptions. First, scaled Schoenfeld residuals are tabulated and plotted in graphical form to test the PH assumption, subsequent to deviance residuals to evaluate influential observations and outliers, and finally the analysis is concluded with the analysis of Martingale residuals to detect nonlinearity.

The PH assumption for Models (1) – (4) is tested with and without industry effects. The results provide an output of the p-value for each covariate and, in the last row, Schoenfeld's global test[19] for the violation of PH assumption, as shown in Tables 5.10 and 5.11.

[19] In the in-sample results, the Schoenfeld global test is also reported. See Section 5.3.3 Table 5.6, Table 5.7, and Table 5.8.

Table 5.10: Schoenfeld's (1982) tests for Model (1) – Model (4)

This table shows Schoenfeld's (1982) global test at a covariate level for Models (1) – (4) without industry effects. A non-significant p-value, $p > 0.10$, indicates that the PH assumption is valid, while p-values of less than 0.05 indicate that the covariate investigated does not meet this assumption. In addition to the per-variable tests, a global chi-square test called χ2 provides a single GOF test statistic. The results provide an output of the p-value for each covariate and, in the last row, Schoenfeld's global test.

	$\chi 2$	df	p
Panel A: Model (1)			
$NITA$	0.67	1	0.41
$TLTA$	1.38	1	0.24
$CASHTA$	0.18	1	0.67
$YEAR$	2.61	1	0.11
$GLOBAL$	5.75	4	0.22
Panel B: Model (2)			
$NITA$	0.00	1	0.98
$TLTA$	2.54	1	0.11
$EXRET$	0.70	1	0.40
$SIGMA$	0.07	1	0.80
$RSIZE$	0.36	1	0.55
$YEAR$	4.09	1	0.05
$GLOBAL$	7.19	6	0.30
Panel C: Model (3)			
$NIMTA$	0.29	1	0.59
$TLMTA$	4.19	1	0.05
$CASHMTA$	0.47	1	0.49
$EXRETAVG$	1.06	1	0.30

	$\chi 2$	df	p
$SIGMA$	0.67	1	0.41
$RSIZE$	2.26	1	0.13
$PRICE$	4.52	1	0.05
MB	1.34	1	0.25
$YEAR$	0.58	1	0.45
$GLOBAL$	9.02	9	0.44
Panel D: Model (4)			
$YEAR$	2.58	1	0.11
$EXRET$	1.23	1	0.27
$PRICE$	0.04	1	0.84
MB	0.69	1	0.40
$SIGMA$	0.00	1	0.96
$EXRETAVG$	0.07	1	0.79
$TLMTA$	0.12	1	0.73
$NIMTA$	0.04	1	0.85
$CASHTA$	0.56	1	0.46
$CASHMTA$	0.28	1	0.60
$GLOBAL$	6.63	10	0.76

[Source: Author’s representation]

Table 5.11: Schoenfeld's (1982) tests for Models (1) IND – (4) IND

This table shows Schoenfeld's (1982) global test at a covariate level for Model (1) – (4) with industry effects. A non-significant p-value, $p > 0.10$, indicates that the PH assumption is valid, while p-values of less than 0.05 indicate that the covariate under investigation does not meet this assumption. In addition to the per-variable tests, a global chi-square test called χ2 provides a single GOF test statistic. The results provide an output of the p-value for each covariate and, in the last row, Schoenfeld's global test.

	$\chi 2$	df	p
Panel A: Model (1) IND			
$NITA$	0.22	1	0.64
$TLTA$	1.18	1	0.28
$CASHTA$	0.21	1	0.65
$YEAR$	2.28	1	0.13
IND	8.37	7	0.30
$GLOBAL$	12.00	11	0.36
Panel B: Model (2) IND			
$NITA$	0.04	1	0.85
$TLTA$	2.60	1	0.11
$EXRET$	0.03	1	0.87
$SIGMA$	0.04	1	0.84
$RSIZE$	0.09	1	0.76
$YEAR$	2.22	1	0.14
IND	3.84	7	0.80
$GLOBAL$	8.47	13	0.81
Panel C: Model (3) IND			
$NIMTA$	0.21	1	0.65
$TLMTA$	4.23	1	0.05

$CASHMTA$	0.23	1	0.63
$EXRETAVG$	1.05	1	0.31
$SIGMA$	1.28	1	0.26
$RSIZE$	2.61	1	0.11
$PRICE$	5.03	1	0.05
MB	1.00	1	0.32
$YEAR$	0.07	1	0.80
IND	10.27	7	0.17
$GLOBAL$	17.79	16	0.34
Panel D: Model (4) $\boldsymbol{IND}$			
$YEAR$	1.49	1	0.22
$EXRET$	0.17	1	0.68
$PRICE$	0.02	1	0.88
MB	0.43	1	0.51
$SIGMA$	0.15	1	0.69
$EXRETAVG$	0.13	1	0.72
$TLMTA$	0.11	1	0.74
$NIMTA$	0.05	1	0.82
$CASHTA$	0.21	1	0.64
$CASHMTA$	0.11	1	0.74
IND	2.49	7	0.93
$GLOBAL$	5.76	17	0.99

[Source: Author's representation]

Listed p-values are used to evaluate the PH assumption more objectively for each covariate in a fitted model. A non-significant p-value, $p > 0.10$, indicates that the PH assumption applies, while a small p-value of less than 0.05 indicates that the tested variable does not satisfy this assumption (Kleinbaum and Klein, 2005, p.

166). In addition to the per-variable tests, a global chi-square test called $\chi 2$, also known as the Schoenfeld global test, is usually performed and provides a single GOF test statistic (Kleinbaum and Klein, 2005, p. 167).

The statistical results show no significant deviation from the proportional hazards assumption for all covariates included. The covariate $YEAR$ in Panel B for Model (2) and the $PRICE$ and $TLTMA$ in Panel C for Models (3) and (3) IND weakly confirm that there is no violation of the PH assumption, as these covariates occur with a p-value of 0.05. Moreover, the results of the Schoenfeld global test suggest that the null hypothesis should be rejected and proportional hazards should be assumed for all fitted models with respective p-values of 0.22 and 0.36 for Model (1), 0.30 and 0.81 for Model (2), 0.44 and 0.34 for Model (3), and 0.76 and 0.99 for Model (4).

After verifying that no covariates arithmetically violate the PH assumption computationally, the next graphical diagnostics of the Schoenfeld individual test is evaluated to check for non-random patterns against time and thus a violation of the PH assumption (Zhang et al., 2018, pp. 5–7). The solid lines in Appendix A-5.4 show smoothing splines. Dotted lines represent a ± 2 standard error confidence band.

Albeit for some of the variables, there is a small noise of systematic deviation from the horizontal line, the horizontal zero-slope lines in the diagrams still do not support a violation of the proportionality assumption. Therefore, the graphical visualization of the Schoenfeld test for the presented models once again does not confirms any violation of the proportional hazard assumption.

Next, dfbeta/dfbetas and deviance residuals are applied to search for outliers and influential data points that could have a significant impact on selected coefficients (Fox and Weisberg, 2018b, p. 16). Applying the argument type=dfbeta to residuals in R yields a matrix of the estimated changes in regression coefficients when each case is deleted in turn (Fox and Weisberg, 2018a, Sec. 8.3.3). Specifying the argument, type=dfbetas in R illustrates the estimated changes of the coefficients divided by their standard errors (Fox and Weisberg, 2018a, Sec. 8.3.3). Finally, deviance residuals can be useful in detecting outliers and are essentially transformed Martingale residuals (Xue and Schifano, 2017, p. 591). The index plots are visualized by performing the above arguments in R and are presented in Appendices A-5.5 to A-5.7 for all regression models performed in this dissertation. Focusing on observation parameters of Models (1) and (1) IND, changes of more than 15% of the standard error of this parameter indicate signs of outliers and influential data points. In $EXRETAVG$, $CASHTA$, and $CASHMTA$, several peaks can be observed, but the dotted blue line, which represents the local average for residuals, does not deviate significantly around the dotted red line to highlight Y= 0 level. Considering that the analysis contains more than 6,622 observations, it can be concluded there are few influential observations. Moreover, if one compares the magnitudes of the largest dfbeta and dfbetas values with the regression coefficients, one can conclude that the plotted data do not represent significant cases of influence and outliers for Models (2) – (4) and Models (2) IND – (4) IND and therefore fulfill the criteria for model fit (Fox and Weisberg, 2018a, Sec. 8.3.3).

Another type of performed residuals are the Martingale residuals plotted against covariates to examine nonlinearity (Xue and Schifano, 2017, p. 588; Fox and Weisberg, 2018b, p. 16). In other words, Martingale residuals evaluate the functional form and fit of covariates, and thus the variable and model fit. Patterns in the plot may indicate that the variable does not fit properly around the dotted red line. Corresponding results, which are shown in Appendix A-5.8 of the Martingale residual detection, are visualized by the dashed blue line and support an indication of linearity.

In summary, the diagnostics of testing the proportional hazards assumption by examining a global and individual Schoenfeld test, the detection of influential observations or outliers by applying dfbeta, dfbetas, and deviance residuals, and the assessment of no non-linearity by Martingale residuals underpins the model fit for Models (2) – (4) and Models (2) IND – (4) IND and appropriateness of the results presented. The diagnostics according to Model (1) and (1) IND performs worse since here the lowest p-values in the Schoenfeld's global test are reached, and subsequent residual analysis shows more significant deviations compared to the other models.

5.4.2 Applying the dynamic AUC for right-censored data

The area under the Receiver Operating Characteristic (ROC) curve, also known as AUC, is used to assess the ability of survival models to predict future risks. In short, "the AUC ratio ranges between 0 and 1" (Ledwon and Jäger, 2020, p. 71). The baseline of 0.5 describes a totally random model. It is important to note that the calculated AUC ratio is adjusted for time-dependency and censoring, as both facets influence the estimated results of survival curves and the coefficients of survival regression analysis (Chambless and Diao, 2006, p. 1). To evaluate the discriminatory power of the Cox regression models used, a recursive calculation of the dynamic AUC for right-censored time-to-event data is performed, as proposed by Chambless and Diao (2006). To distinguish the out-of-sample models, the sample "is divided into training and testing samples with a 70% to 30% data partition. The *iauc* summary is given by the integral of AUC at [1,19] weighted by the estimated probability density of the time-to-event outcome" (Ledwon and Jäger, 2020, p. 62), as shown in Table 5.12, and is used as the primary measure to analyze the discriminatory power of fitted models. When comparing the two time-dependent AUC curves over the entire above-mentioned integral, a Wilcoxon rank-sum test is applied to dependent samples and is shown in Table 5.13. In short, the respective output shows the p-values for the null hypothesis of AUC values for any pair of models (Haibe-Kains et al., 2008, p. 2200). In accordance with Haibe-Kains et al. (2008), the two vectors of AUCs compared are based on the same survival data and the respective points in time.

Table 5.12: AUC for right-censored time-to-event data for Models (1) – (4)

This table contains the results of calculated dynamic AUC for the right-censored time-to-event data proposed by Chambless and Diao (2006). To distinguish out-of-sample models, the data set is divided into a training and testing sample with a 70% to 30% data partition, with company identification remembered. The summarizing *iauc* measure is given by the integral of the AUC at [1,19], weighted by the estimated probability density of the time-to-event outcome. In addition, summary statistics of calculated AUC ratios are provided.

AUC	*iauc*	Mean	Median	Min.	Max.	Std. Dev.
Model (1)	0.64	0.86	0.90	0.64	1.00	0.13
Model (1) ***IND***	0.65	0.86	0.90	0.65	0.99	0.13
Model (2)	0.85	0.91	0.90	0.85	1.00	0.05
Model (2) ***IND***	0.88	0.93	0.92	0.87	1.00	0.04
Model (3)	0.89	0.86	0.84	0.83	0.97	0.05
Model (3) ***IND***	0.89	0.88	0.86	0.84	0.98	0.04
Model (4)	0.89	0.91	0.89	0.85	1.00	0.05
Model (4) ***IND***	0.90	0.93	0.91	0.88	0.99	0.04

[Source: Author's representation]

In addition to the AUC ratios in tabular form, Figure 5.5 shows graphical visualization for fitted models. Black lines illustrate the AUC for models without industry grouping, while red lines show the AUC for models with industry grouping. Model (1) represents a weak discriminatory power of the *iauc* of 0.64 without industry grouping, coupled with a relatively high standard deviation of 0.13. The inclusion of industry grouping slightly improves discriminatory power to 0.65. Model (2) assures with an *iauc* of 0.87 that the high discriminatory power increases slightly when the industry grouping (0.88) is added. Model (3) presents upper-level results with a superior *iauc* of 0.89. On the basis of the stepwise selected Model (4), the best discriminatory results in the class are given with an *iauc* of 0.89 without and 0.90 with industry grouping.

In summary, there is a minor improvement in the industry grouping when considering accounting ratios and the hybrid approach by Shumway (2001) which uses accounting and market-based predictors. Moreover, the discriminatory power increases with increasing time intervals. During the period of the discontinued *Neuer Markt* segment in 2002, all four models showed deficits in the accuracy of survival and insolvency forecasts, as many of the companies included in the study voluntarily switched to the regulated market before filing for insolvency proceedings. Comparing the out-of-sample results with Chava and Jarrow (2004), a marginal improvement in discriminatory power is visualized below for the non-financial German companies represented in the CDAX.

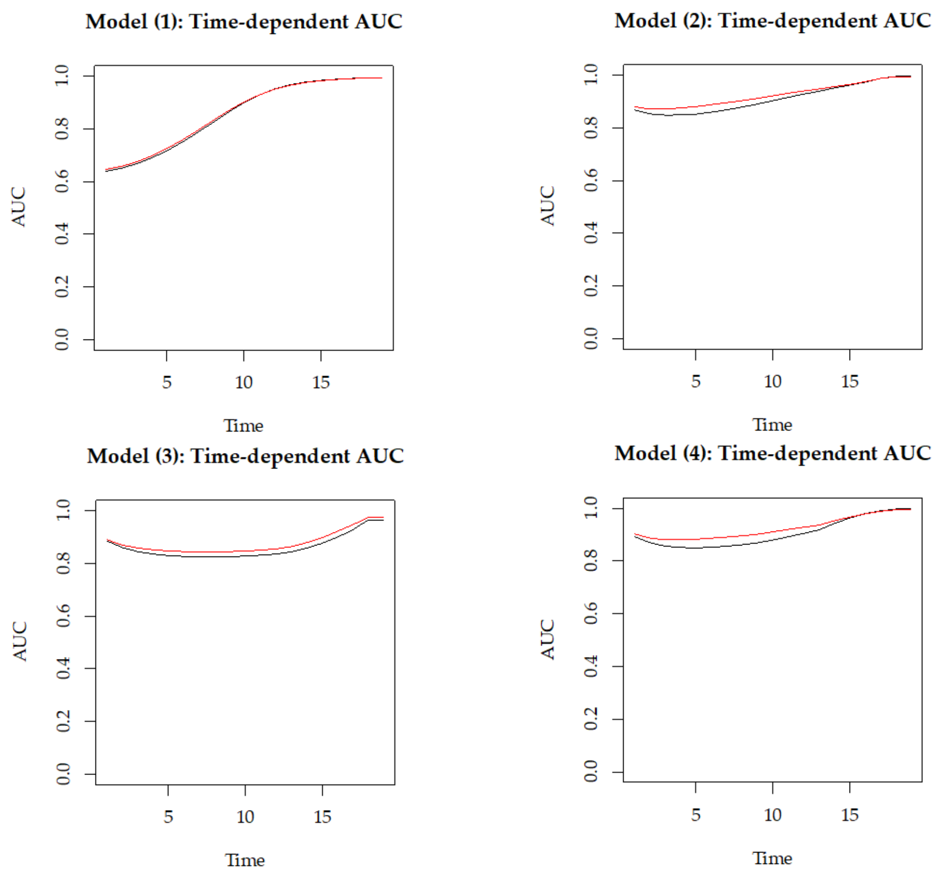


Figure 5.5: Time-dependent AUC for Models (1) – (4)
[Source: Author's representation]

A comparison of the statistical effect of the inclusion of industry variables in relation to the $iauc$ is further analyzed by applying the Wilcoxon rank-sum test for dependent samples (Haibe-Kains et al., 2008, p. 2200). The results show that the IND of Model (1) is statistically different ($p < 0.05$), and the other Models (2) – (4), when IND is included, show evidence at the significance level ($p < 0.01$). In terms of a general model comparison, Model (2) differs statistically from the other models, indicating superior discriminatory power.

Table 5.13: Wilcoxon rank-sum test of calculated AUC for Models (1) – (4)

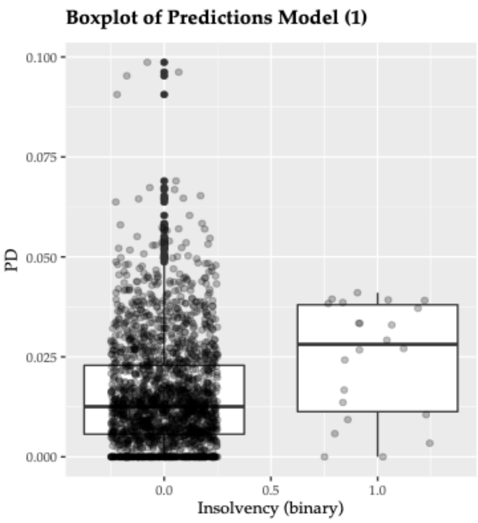
In this table, the $iauc$ is represented by the results of the time-dependent ROC curves. The statistical test is a Wilcoxon rank-sum test for dependent samples.

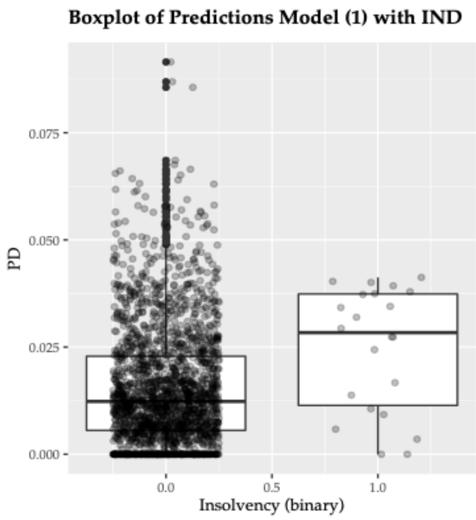
	Model (1)	**Model (1) IND**	**Model (2)**	**Model (2) IND**	**Model (3)**	**Model (3) IND**	**Model (4)**	**Model (4) IND**
Model (1)		0.98	0.97	0.99	0.52	0.69	0.90	0.97
Model (1) IND	0.02**		0.96	0.69	0.46	0.63	0.90	0.96
Model (2)	0.03**	0.04**		1.00	0.00***	0.00***	0.07**	1.00
Model (2) IND	0.01***	0.01***	0.00***		0.00***	0.00***	0.00***	0.14*
Model (3)	0.49	0.56	1.00	1.00		1.00	1.00	1.00
Model (3) IND	0.32	0.38	1.00	1.00	0.00***		1.00	1.00
Model (4)	0.10**	0.10**	0.93	1.00	0.00***	0.00***		1.00
Model (4) IND	0.03**	0.04**	0.00***	0.87	0.00***	0.00***	0.00***	

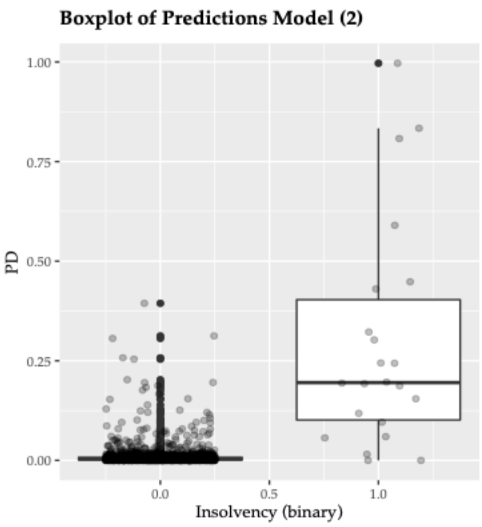
Note: *** p<0.01, ** p<0.05, * p<0.1.

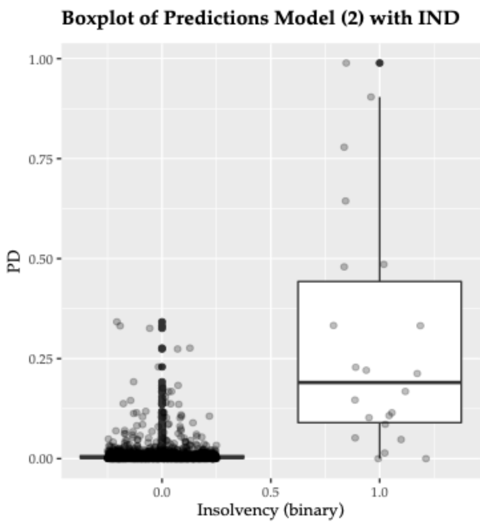
[Source: Author’s representation]

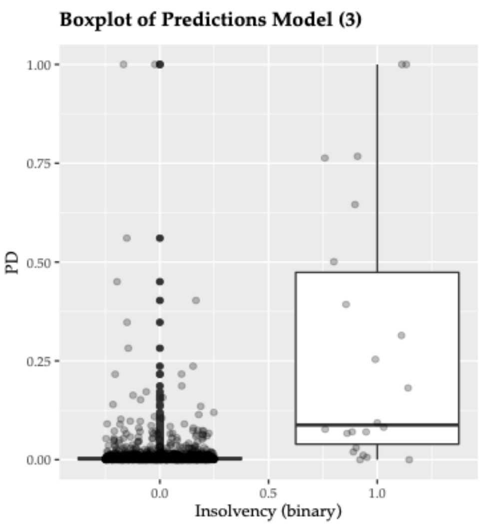
Since one objective of this dissertation is to assess the discriminatory power of tested PD models, box plots are used to highlight the sensitivity of predictions. In order to compute Figure 5.6, one need to derive predicted PD as follows. "As the probability of survival for a subject is equal to exp(-expected value), predicted PD is equal to 1-exp(-expected value)" (Ledwon and Jäger, 2020, p. 62). The black bars show the median, while the edges of each box provide the 25th and the 75th percentiles. In short, a well-functioning model should not show any overlap in the predictions of the binary-coded event variables insolvency. Nevertheless, the weak discriminatory power of Model (1) is reassured in comparison to the results of Models (2), (3), and (4). The inclusion of industry grouping shows no far-reaching shifts in the presented boxplots.

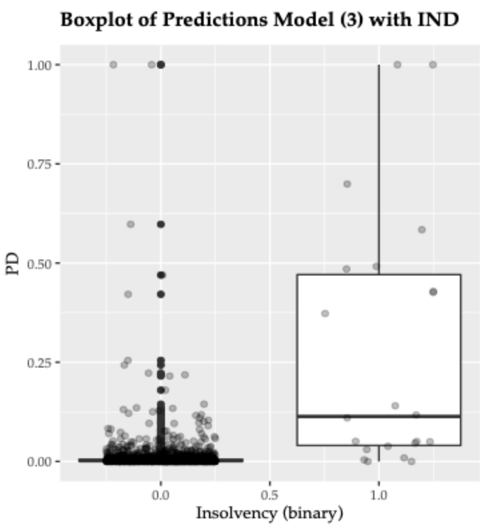





Boxplot of Predictions Model (2)
PD
1.00
0.75
0.50
0.25
0.00
0.0
0.5
1.0
Insolvency (binary)


Boxplot of Predictions Model (2) with IND
PD
1.00
0.75
0.50
0.25
0.00
0.0
0.5
1.0
Insolvency (binary)


Boxplot of Predictions Model (3)
PD
1.00
0.75
0.50
0.25
0.00
0.0
0.5
1.0
Insolvency (binary)


Boxplot of Predictions Model (3) with IND
PD
1.00
0.75
0.50
0.25
0.00
0.0
0.5
1.0
Insolvency (binary)

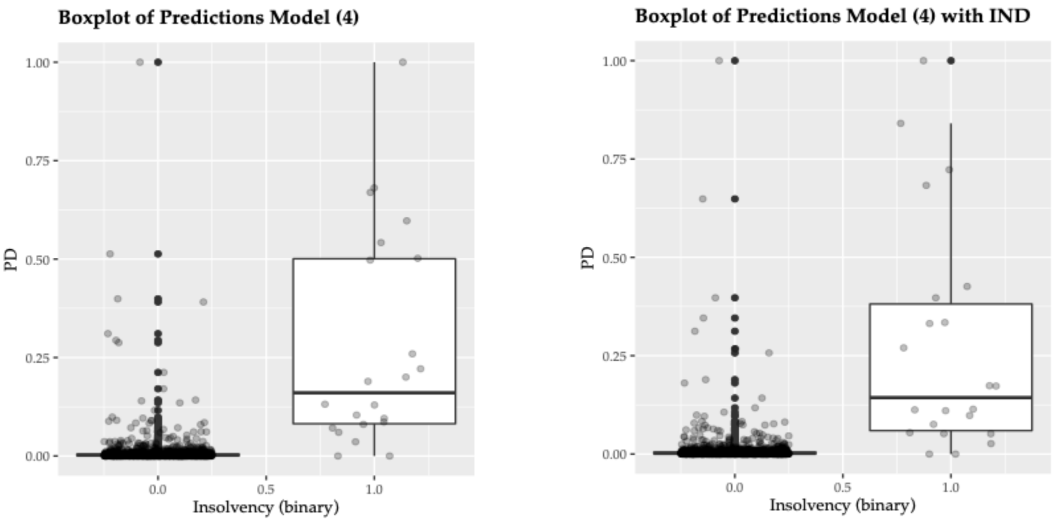


Figure 5.6: Boxplots of predictions for Models (1) – (4)
[Source: Author's representation]

5.4.3 Performing walk-forward analysis

According to Sobehart, Keenan, and Stein (2000), "the performance statistics for credit risk models can be highly sensitive to the data sample used for validation" (Sobehart, Keenan, and Stein, 2000, p. 7). Since the above model discrimination measures were based on a training and testing sample, this section presents a decile ranking based on the state-of-the-art walk-forward analysis proposed by Sobehart, Keenan, and Stein (2000) for out-of-sample out-of-time predictions. The main purpose of this analysis is a rigorous model calibration, which allows a quantitative model comparison.

> "The result set of the expanding estimations is utilized to perform model calibration. A well-calibrated PD model should provide high accuracy rates (AR) in top deciles. Following Shumway (2001) and Chava & Jarrow (2004), the firms with the highest probability of default in each year are placed into the first decile in descending order. Secondly, year by year, beginning from 2002, … the number of firms in each decile that .. filed for insolvency [in the past is taken into account]" (Ledwon and Jäger, 2020, p. 73).

The number of companies in each decile that filed for insolvency in the entire study from 2002[20] to 2018 is aggregated in the result set, and for each decile, the percentage of insolvent companies in that decile is shown in Table 5.14 and visually displayed in Figure 5.7. A traffic-light color palette is created to clearly highlight the model calibration.

Table 5.14: Model calibration and decile ranking

This table reports accuracy rates (AR) per decile of correctly predicted insolvencies in the out-of-sample out-of-time validation study from 2002 until 2018 following the walk-forward procedure suggested by Sobehart, Keenan, and Stein (2000). Based on the computed result set, PDs are binned into 10 equally sized deciles in descending order.

Decile	AR Model (1) (%)	AR Model (1) with IND (%)	AR Model (2) (%)	AR Model (2) with IND (%)	AR Model (3) (%)	AR Model (3) with IND (%)	AR Model (4) (%)	AR Model (4) with IND (%)
1	25.27	25.27	97.80	97.80	93.41	90.11	97.80	97.80
2	18.68	17.58	1.10	1.10	3.30	6.59	0.00	1.10
3	18.68	12.09	0.00	0.00	1.10	2.20	1.10	0.00
4	8.79	19.78	0.00	0.00	1.10	0.00	0.00	0.00
5	7.69	7.69	0.00	0.00	0.00	0.00	0.00	0.00
6	4.40	3.30	0.00	0.00	0.00	0.00	0.00	0.00
7	5.49	4.40	0.00	0.00	0.00	0.00	0.00	0.00
8	2.20	3.30	1.10	1.10	0.00	0.00	0.00	0.00
9	6.59	4.40	0.00	0.00	1.10	0.00	1.10	1.10
10	2.20	2.20	0.00	0.00	0.00	1.10	0.00	0.00

[Source: author's representation]

[20] 2002 has been selected as first year of forecasts to avoid any adverse effects on results due to a small number of events.

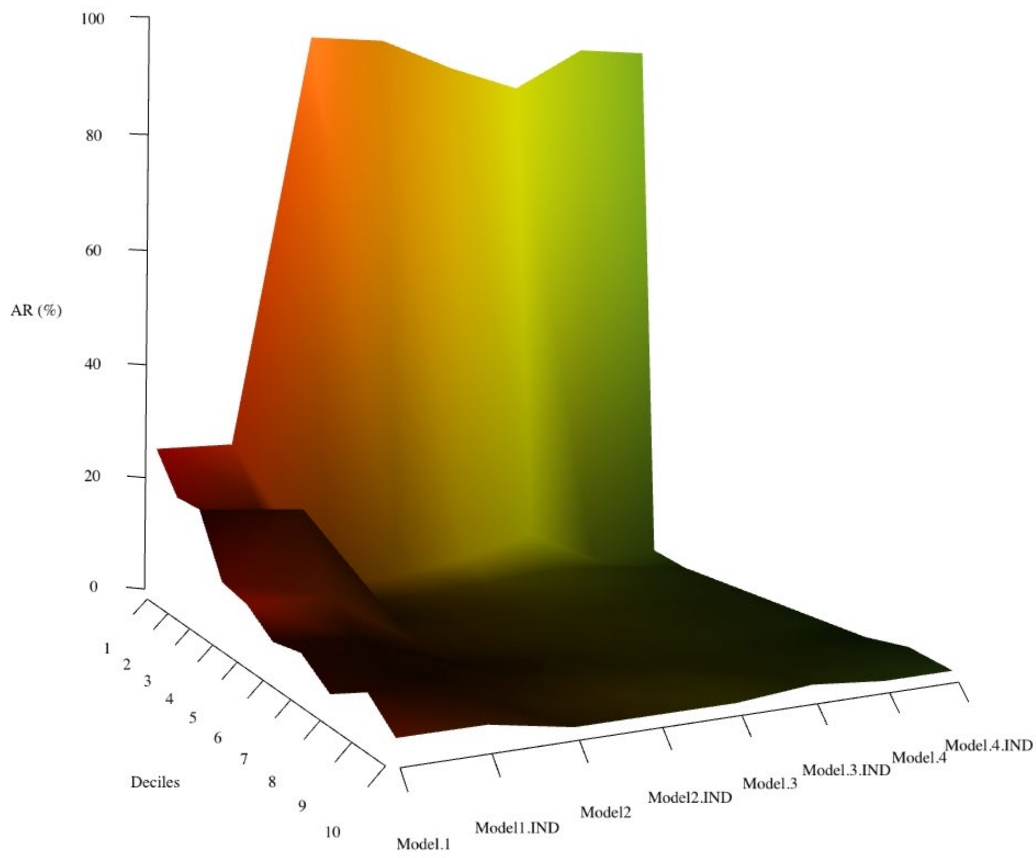


Figure 5.7: Model calibration and decile ranking
[Source: Author's representation]

A well-calibrated model should have the following characteristics. First, a strong waterfall effect should be visible since the AR of correctly predicted insolvencies in the out-of-sample out-of-time validation study should be the highest in decile 1 and lowest in decile 10. Second, a flat AR in all deciles indicates a completely random model, and jumping ARs indicate a severe miscalibration (Chava and Jarrow, 2004, p. 549; Mertens, Poddig, and Fieberg, 2018, p. 37).

Model (1) shows a severe miscalibration, which is clearly highlighted by the red area in Figure 5.7. "In the first decile, only 25.27% of insolvencies are correctly identified" (Ledwon and Jäger, 2020, p. 74). Furthermore, no decreasing effect can be made visible since the AR increases in the course of deciles 3 and 4. If one focuses on insolvent companies above the probability median, 79.12% of insolvencies are correctly estimated. "Including industry grouping, … an increase in accuracy rates of 3.30%, .. [with] 82.42% [being achieved] in the top 5 deciles" (Ledwon and Jäger, 2020, p. 74). The color ramp shown in Figure 5.7 moves slightly from red to the orange area, which still indicates an incorrect calibration. Thus,

> "Model (1) ranks 20.88% and 17.58% of estimated insolvencies within deciles 6-10. Hence, out-of-sample calibration reassures the weak discriminatory power. Following Shumway (2001) variable selection of accounting-based and market-driven covariates in Model (2) leads to 97.80% correct predictions in the first decile with and without industry grouping and 98.90% in top deciles" (Ledwon and Jäger, 2020, p. 74).

Figure 5.7 shows significant improvements in surface and color. Following the market-oriented approach of Campbell, Hilscher, and Szilagyi (2008), "Model (3) confirms high accuracy rates in the top decile of 93.41% and 90.11%. Within [the] top 5 deciles, Model (3) [also] confirms with and without industry grouping accuracy rates of 98.90%" (Ledwon and Jäger, 2020, p. 74). Nonetheless, there is no improvement in calibration results when the industry grouping is included, and therefore, a yellow area is shown in Figure 5.7. As expected, the stepwise selected Model (4) again confirms high accuracy rates with 97.80% correct predictions in the first decile, with and without industry grouping, and 98.90% in the top deciles, which are highlighted in green.

5.5 COMPARISON WITH EXISTING STUDIES AND HYPOTHESIS TESTING

With the preceding estimation of extended Cox proportional hazards, the regression analysis for non-financial entities in Germany, and corresponding out-of-sample tests, the comparison of the results obtained with earlier studies is of particular interest. A great deal of research has focused on the assessment of corporate defaults. In this context, diverging methodologies and data differences were discussed in the literature review in Chapter 4.1. This chapter then focuses mainly on the potential differences in the results as well as newly discovered evidence resulting from this research.

First, the fitted out-of-sample Models (1) – (4) are compared with the leading alternatives in terms of mean AUC ratios in order to further validate the empirical results. Table 5.15 shows the benchmark results. Since this dissertation carries out a time-dependent AUC analysis proposed by Chambless and Diao (2006), the *iauc* is given in parentheses, which accounts for right-censoring. However, comparable studies report on the mean AUC. To ensure comparability, the corresponding outputs are shown in Table 5.15. Second, the model calibration measure of the accuracy rate (AR) in the top decile, according to the walk-forward analysis, is compared with existing studies in Table 5.16.

In view of the fact that most PD studies are based on U.S. data, the dynamic logit model for the German market, applied by Mertens, Poddig, and Fieberg (2018), seems to be a reasonable starting point for benchmarking. Despite a similar methodological approach and study design, the works differ in certain aspects. First, Mertens, Poddig, and Fieberg (2018) consider a longer time horizon from 1991 to 2015. In contrast, the research conducted in this dissertation uses an up-to-date, unbalanced panel data set from 2000 to 2018, which records the insolvencies of recent years under the influence of the ESUG. Since InsO came into force in 1999, the initial year for determining insolvency has been set at 2000. The selected approach is in accordance with the identification of the sample proposed by Hillegeist et al. (2004), which aims to capture insolvency characteristics taking into account important statutory changes. A further distinction between this dissertation and Mertens, Poddig, and Fieberg (2018) is the sample size of active non-financial companies, which differs considerably, as the latter takes into account all non-financial equity listings in Frankfurt. In contrast, this dissertation imitates the CDAX in order to capture the regulated German equity market in its entirety. The index is particularly suitable for research and empirical analysis due to the more efficient and transparent availability of data (Deutsche Börse Group, 2004, p. 5). Considering the difference in sample size and orientation, Mertens, Poddig, and Fieberg (2018) propose to use the variable selection of Campbell, Hilscher, and Szilagyi (2008) as a benchmark model for Germany to achieve an

AUC of 0.85. This dissertation validates a high AUC ratio of 0.86 ($iauc$ 0.89) for Model (3), which builds on the set of covariates proposed by Campbell, Hilscher, and Szilagyi (2008). However, at the significance level ($p < 0.01$), the Wilcoxon rank-sum test indicates that the selection of variables proposed by Shumway (2001) and presented in Model (2) differs statistically from the other Models (1) and (3). Model (2) indicates superior discriminatory power. In this context, the empirical results and time-dependent AUC analysis show that a mixture of pure accounting information and market-driven indicators in Model (2) has a high discriminatory power with an average AUC of 0.91 and an $iauc$ of 0.85.

Furthermore, the stepwise variable selection procedure shown in Model (4), with an average AUC of 0.91 and an $iauc$ of 0.89 shows the best results in the class. With regard to assessing model calibration, Mertens, Poddig, and Fieberg (2018) carry out a decile ranking in which they recommend the variable selection of Campbell, Hilscher, and Szilagyi (2008) as the best-calibrated model. The results in Table 5.16 again confirm high calibration results for Model (3), but the variable selection by Shumway (2001) of the accounting-based and market-driven variables presented in Model (2) results in higher-ranked accuracy rates in the top decile with 97.80% correct predictions.

Subsequently, a comparison to Chava and Jarrow (2004) is conducted, taking industry effects into account. The authors suggest that the industry grouping significantly improves the forecast results because the industry variables are statistically significant in-sample. Nonetheless, the inclusion of industry effects only slightly improves the reported AUC ratio for non-financial public enterprises from 0.90 to 0.91 (Chava and Jarrow, 2004, p. 558). Table 5.15 shows only minor improvements when categorial industry groupings are added according to SIC. However, hypotheses tests for $\boldsymbol{H_{3a}}$ show statistical significance for the comparison of time-dependent $iauc$. A comparison of the statistical effect of including industry variables in relation to the $iauc$ is analyzed by applying the Wilcoxon rank-sum test for dependent samples (Haibe-Kains et al., 2008, p. 2200). The results show that the IND of Model (1) is statistically different ($p < 0.05$), and other Models (2) – (4), when the IND is included, show evidence at the significance level ($p < 0.01$). Furthermore, no general improvement in accuracy rates can be observed if market variables are already included in the PD model, as highlighted in Table 5.16. Comparison of the results of the models with the best performance in the empirical part of this dissertation with the original U.S. studies from Shumway (2001) and Campbell, Hilscher, and Szilagyi (2008) indicate superior discriminatory power and satisfactory calibration results when appropriate validation techniques have been applied.

Table 5.15: AUC benchmark

This table provides an overview of discrimination results from the related literature compared to the empirical discrimination results in this dissertation. The mean AUC is given to ensure comparability with previous studies, and the *iauc* is given in parentheses, which accounts for right-censoring.

Benchmark model discrimination	Mean AUC
Shumway (2001)	n/a
Chava and Jarrow (2004)	0.91
Campbell, Hilscher, and Szilagyi (2008)	n/a
Mertens, Poddig, and Fieberg (2018)	0.85
Model (1)	0.86 (*iauc* 0.64)
Model (1) IND	0.86 (*iauc* 0.65)
Model (2)	0.91 (*iauc* 0.85)
Model (2) IND	0.93 (*iauc* 0.88)
Model (3)	0.86 (*iauc* 0.89)
Model (3) IND	0.88 (*iauc* 0.89)
Model (4)	0.91 (*iauc* 0.89)
Model (4) IND	0.93 (*iauc* 0.90)

[Source: Author's representation]

Table 5.16: Top decile accuracy rate (AR) benchmark

This table gives an overview of calibration results from the related literature compared to empirical calibration results in this dissertation. Accuracy rates (AR) are given in percent for the top decile.

Benchmark Model Calibration	AR in top decile (%)
Shumway (2001)	75.00
Chava and Jarrow (2004)	74.40
Campbell, Hilscher, and Szilagyi (2008)	86.20
Mertens, Poddig and Fieberg (2018)	63.95
Model (1)	25.27
Model (1) IND	25.27
Model (2)	97.80
Model (2) IND	97.80
Model (3)	93.41
Model (3) IND	90.11
Model (4)	97.80
Model (4) IND	97.80

[Source: Author’s representation]

The next paragraph draws conclusions on each hypothesis developed in Chapter 5.1 and related tests and validation techniques applied in Chapter 5.4.

H$_{1a}$: *The market-based variable selection proposed by Campbell, Hilscher, and Szilagyi (2008) in Model (3) shows a statistical improvement in the discriminatory power of fitted PD models compared to a hybrid approach proposed by Shumway (2001) in Model (2) and a parsimonious accounting-based approach inspired by covariates recommended by Altman (1968) and Ohlson (1980), among others, in Model (1).*

H$_{2a}$: *The market-based variable selection proposed by Campbell, Hilscher, and Szilagyi (2008) in Model (3) shows an improvement in the accuracy rates of fitted PD models compared to a hybrid approach proposed by Shumway (2001) in Model (2) and a parsimonious accounting-based approach inspired by covariates recommended by Altman (1968) and Ohlson (1980), among others, in Model (1).*

In summary, the calculated results lead to fail to reject the null hypotheses for $\boldsymbol{H_{1a}}$ and $\boldsymbol{H_{2a}}$ since the market-based variable selection proposed by Campbell, Hilscher, and Szilagyi (2008), does not show any general improvement in terms of discriminatory power and accuracy rates of fitted PD models compared to a hybrid approach proposed by Shumway (2001). Therefore, this thesis recommends the use of a mixture of pure accounting indicators with market-driven ratios as in Model (2). This covariates selection shows a simple approach to achieving superior performance in the top deciles during out-of-sample calibration. However, in-sample empirical results underline the importance of market-based indicators, as all accounting ratios become statistically insignificant.

$\boldsymbol{H_{3a}}$: *The inclusion of a categorial industry grouping according to the four-digit Standard Industrial Classification (SIC) improves the statistical discriminatory power of fitted PD models of accounting-based and market-based indicators in Models (1) – (4) IND.*

$\boldsymbol{H_{4a}}$: *The inclusion of a categorial industry grouping according to the four-digit Standard Industrial Classification (SIC) improves the forecast accuracy of fitted PD models of accounting-based and market-based indicators in Models (1) – (4) IND.*

$\boldsymbol{H_{3a}}$ rejected the null in favor of the alternative hypothesis. There is enough evidence to reject the null hypothesis. A comparison of the statistical effect of the inclusion of industry variables with respect to the $iauc$ is analyzed by applying the Wilcoxon rank-sum test for dependent samples. The results show that the IND of Model (1) is statistically different ($p < 0.05$), and the other Models (2) – (4), when IND is included, show evidence at the significance level ($p < 0.01$). $\boldsymbol{H_{4a}}$ results in the null hypothesis not being rejected because the walk-forward model validation does not signal general improvements in accuracy rates when the IND is included.

$\boldsymbol{H_{5a}}$: *The stepwise variable selection procedure for Cox's proportional hazards model with forward and backward iterations steps statistically improves the discriminatory power of the fitted PD models presented in Models (4) and (4) IND.*

H_{6a}: *The stepwise variable selection procedure for Cox's proportional hazards model with forward and backward iterations steps improves accuracy rates of the fitted PD models Models (4) and (4) IND.*

H_{7a}: *Since the inception of ESUG in 2012, a statistically significant decrease in the hazard ratio should be observed in relation to the fitted interaction. Companies that implement ESUG measures according to InsO Sections 270a and 270b should be associated with a healthier financial situation and thus reduce the risk of filing for insolvency if all other covariates shown in Model (1) – (4) ESUG are kept constant.*

H_{5a} leads to fail to reject the null hypothesis because the application of the Wilcoxon rank-sum test for dependent samples $iauc$ test results for Models (4) and (4) IND give statistically different results ($p < 0.05$) compared to Models (1) and (3) only. However, the comparison with Model (2) and Model (2) IND shows no statistically significant evidence ($p > 0.05$). With reference to the stepwise variable selection presented in Model (4), it can be concluded the calibration results are the best in class, but no improvement is achieved over the $iauc$ result of Model (2), and therefore, ***H_{6a}*** cannot reject the null hypothesis.

To the best of the author's knowledge, there is as yet no comparison with existing studies that examine the effects of the inception of ESUG on the default risk of German non-financial companies. Therefore, no further validation with quantitative studies can be completed. In short, ***H_{7a}*** leads the null hypothesis not being rejected because the in-sample interaction terms presented do not provide robust results and violate the PH assumptions. Particularly due to the low proportion of verified insolvency cases under the ESUG, the respective results have to be interpreted with caution. In summary, it can be said that decreasing hazard rates only exist for the interaction term with regard to $ESUG{:}\,NITA$ and $ESUG{:}\,NIMTA$.

5.6 CONCLUSION

The empirical analysis of this dissertation is presented in this chapter and its structure is distinctly visualized in Figure 5.1. First, the development of adequate research hypotheses and their economic context will be addressed. In summary, (1) the importance of accounting and financial ratios, as well as (2) industry effects, helpful in identifying potential insolvencies, are derived as main objectives. When applying the enhanced semiparametric Cox proportional hazards regression analysis, (3) the stepwise variable selection procedure with forward and backward iterations aims at statistically improving empirical results of fitted PD models and presenting the computationally best candidate final regression model. Finally, (4) the introduction of the ESUG will be quantitively tested in accordance with its objective, namely, to enter insolvency proceedings in a healthier state. After the operationalization of the respective research hypotheses in Chapter 5.1, descriptive statistics and non-parametric survival analyses, as well as mandatory data adjustment measures and a presentation of the explanatory variables used, are carried out in Chapter 5.2. The main part of the empirical analysis consists of in-sample empirical results, model diagnostics, and GOF measures, namely a demonstration of the time-dependent AUC analysis by Chambless and Diao (2006), and the application of a walk-forward analysis in accordance with by Sobehart, Keenan, and Stein (2000) to enable a decile ranking as the main validation technique. In Chapter 5.5, the empirical findings of this dissertation are related to previous studies, several sets of benchmarks are proposed, and some conclusions are drawn for each hypothesis developed. Table 5.17 provides an overview of the theory-based hypotheses, the tests applied, and the conclusions drawn.

Table 5.17: Summary of hypothesis testing

This table shows the results of the derived research hypotheses, divided into applied tests, level of acceptance, and results with cross-references.

Tests	Acceptable level	Results
H1a: *The market-based variable selection proposed by Campbell, Hilscher, and Szilagyi (2008) in Model (3) shows statistical improvement in the discriminatory power of fitted PD models compared to a hybrid approach proposed by Shumway (2001) in Model (2) and a parsimonious accounting-based approach inspired by covariates recommended by Altman (1968) and Ohlson (1980), among others, in Model (1).*		
Schoenfeld global test	$p > 0.10$	Yes, Models (1) – (3) show no violation of the PH assumption.
Deviance residuals	$Y = 0$	Yes, no serious influential observations in Models (2) and (3). More significant deviations exist in Model (1).
Martingale residuals	$Y = 0$	Yes, no strong non-linearity in Models (2) and (3). More significant deviations exist in Model (1).
Likelihood ratio test	$p < 0.05$	Yes, in-sample empirical results show the respective acceptance level for Models (1) – (3).
Wald test	$p < 0.05$	Yes, in-sample empirical results show the respective acceptance level for Models (1) – (3).
Score (log-rank) test	$p < 0.05$	Yes, in-sample empirical results show the respective acceptance level for Models (1) – (3).
Concordance	0.5 (random fit) to 1 (perfect fit)	0.97 in Models (2) and (3). 0.64 in Model (1).
$iauc$	0.5 (random fit) to 1 (perfect fit)	0.64 Model (1), 0.85 Model (2), and 0.89 Model (3).

Tests	Acceptable level	Results
Wilcoxon rank-sum test	$p < 0.05$	No, as Model (3) and (1) $p > 0.05$. Only Model (2) shows significant $p < 0.05$.

***H*$_{2a}$:** *The market-based variable selection proposed by Campbell, Hilscher, and Szilagyi (2008) in Model (3) shows a statistical improvement in the accuracy rates of fitted PD models compared to a hybrid approach proposed by Shumway (2001) in Model (2) and a parsimonious accounting-based approach inspired by covariates recommended by Altman (1968) and Ohlson (1980), among others, in Model (1).*

Walk-forward analysis and decile ranking	Accuracy rate (AR) in > 75% in top decile at an acceptable level. Highest AR as a hypothesis test	No, because of 93.41% in Model (3) vs. 97.80% in Model (2), and 25.27% in Model (1).

***H*$_{3a}$:** *The inclusion of a categorical industry grouping according to the four-digit Standard Industrial Classification (SIC) improves the statistical discriminatory power of fitted PD models of accounting-based and market-based indicators in Models (1) – (4) IND.*

Schoenfeld global test	$p > 0.10$	Yes, Models (1) – (4) *IND* shows no violation of the PH assumption.
Deviance residuals	$Y = 0$	Yes, no serious influential observations in Models (2) – (4) *IND*. More significant deviations exist in the Model (1) *IND.*
Martingale residuals	$Y = 0$	Yes, no strong non-linearity in Models (2) – (4). More significant deviations exist in Model (1) *IND*.
Likelihood ratio test	$p < 0.05$	Yes, in-sample empirical results show the respective acceptance level for Models (1) – (4) *IND*.
Wald test	$p < 0.05$	Yes, in-sample empirical results show the respective acceptance level for Models (1) – (4) *IND*.

Tests	Acceptable level	Results
Score (log-rank) test	$p < 0.05$	Yes, in-sample empirical results show the respective acceptance level for Models (1) – (4) *IND*.
Concordance	0.5 (random fit) to 1 (perfect fit)	0.66 Model (1) *IND*, 0.98 Model (2) *IND,* 0.97 Model (3) *IND*, and 0.98 in Model (4) *IND*.
iauc	0.5 (random fit) to 1 (perfect fit)	0.65 Model (1), 0.88 Model (2), and 0.89 Model (3).
Wilcoxon rank-sum test	$p < 0.05$	Yes, because Models (1) – (4) *IND* show significant $p < 0.05$.
H_{4a}: *The inclusion of categorial industry grouping according to the four-digit Standard Industrial Classification (SIC) improves the forecasting accuracy of fitted PD models of accounting-based and market-based indicators Model (1) – (4) IND.*		
Walk-forward analysis and decile ranking	Accuracy rate (AR) in > 75% in top decile at an acceptable level. Highest AR as a hypothesis test	No, because of unchanged AR with 25.27% in Model (1) *IND* 97.80% in Model (2) *IND*, and 97.80% in Model (4) *IND*. Model (3) *IND* shows decreasing values 90.11% vs. 93.41%.
H_{5a}: *Stepwise variable selection procedure for Cox's proportional hazards model with forward and backward iterations steps statistically improves the discriminatory power of the fitted PD models presented in Models (4) and (4) IND.*		
Wilcoxon rank-sum test	$p < 0.05$	No, as Model (4) shows $p < 0.05$ compared to fitted Models (1) and Model (3). In comparison to Model (2) and Model (2) *IND*, no significant p-value is present.
H_{6a}: *Stepwise variable selection procedure for Cox's proportional hazards model with forward and backward iterations steps improves the accuracy rates of the fitted PD models presented in Models (4) and (4) IND.*		
Walk-forward analysis and decile ranking	Accuracy rate (AR) in > 75% in top decile at an acceptable level.	No, only best-in-class results are confirmed (97.80% in Model (4) vs. 97.80% in Model (2) in the top decile.

Tests	Acceptable level	Results
	Highest AR as a hypothesis test	
H_{7a}: *Since the inception of the ESUG in 2012, a statistically significant decline in hazard ratio should be observed in relation to the fitted interaction. Companies that implement ESUG measures according to InsO Sections 270a and 270b should be associated with a healthier financial situation and therefore have a lower risk of filing for insolvency if all other covariates constant presented in Models (1) – (4) $ESUG$* are kept constant.		
Hazard ratios of computed interaction terms.	A decrease in hazard ratios compared to the base models.	No, the majority of interaction terms provide counter-intuitive results or cannot be further commented on due to a wide range of confidence intervals. In addition, all models except Model (4) $ESUG$ violate the PH assumption. In particular, the low proportion of verified insolvency cases under the ESUG does not provide robust and valid results to continue model discrimination and validation techniques. In summary, only for the interaction term in relation to $ESUG: NITA$ and $ESUG: NIMTA$, one can conclude that hazard rates are decreasing.

[Source: Author's representation]

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6 SUMMARY

Although the prediction of corporate insolvencies and defaults has been thoroughly investigated and methodologically developed over the last 50 years, the majority of research contribution has been devoted to U.S. samples. From this literature, competing empirical models with varying explanatory variables and different statistical methods for model estimation have evolved. This dissertation forecasts corporate insolvency using an enhanced Cox proportional hazards regression model with explanatory variables constructed from accounting and market-based ratios that have proven to be key explanatory indicators in previous studies. A total of 15 ratios were prepared using the yearly data from TDS. Model (1) is inspired by Altman (1968) and Ohlson (1980). Model (2) follows Shumway (2001) and estimates a model that considers assets in the traditional way, using book values. The approach of Campbell, Hilscher, and Szilagyi (2008) in Model (3) is applied, inter alia, in adjusting book values to market-driven variables. Since the aforementioned model constellations are based on a comprehensive literature review, the stepwise variable selection procedure in Model (4) is used to obtain the best candidate final regression model.

In addition, this dissertation tests the effect of industry variables on the discriminatory power and forecasting accuracy of the fitted models. Surprisingly, the industry effects have not received much attention so far in the relevant academic literature. According to Chava and Jarrow (2004), an industry grouping should improve the discriminatory power since divergent levels of competition between industries and different accounting conventions, as well as regulatory requirements, should influence the likelihood of insolvency cases.

Finally, this dissertation aims to examine the effects of regulatory changes in insolvency law. According to the ESUG, a key objective is to offer new strategic options for overcoming a crisis situation and to make a change towards insolvency proceedings that promote a continuation-oriented approach.

6.1 SCIENTIFIC AND MANAGERIAL IMPLICATIONS

Based on the recent research contribution, this dissertation focused on applying a novel methodology in the field of default prediction, namely Cox proportional hazards regression models, considering the Andersen-Gill counting process (AG-CP), to account for right-censoring and time-dependent covariates. Models (2) and (3) with market-based predictors suggested by Shumway (2001) and Campbell, Hilscher, and Szilagyi (2008) proved to show the most precise results in terms of model discrimination and calibration. The proposed Model (4), which is based on a stepwise variable selection procedure, provides superior GOF measures and discriminatory power, as well as satisfactory validation results comparable to Model (2).

First, it is not appropriate to rely on a sparse accounting-based approach. The set of exogenous predictors, which include those presented by Altman (1968) and Ohlson (1980), show the least accurate discriminatory power in the empirical analysis, presented in Model (1). The walk-forward testing performed confirms a serious miscalibration. Moreover, nonlinearity was detected in the model diagnostics.

Second, the variable selection by Shumway (2001) and Campbell, Hilscher, and Szilagyi (2008) provides superior results for companies listed in Germany with high *iauc* ratios. While Mertens, Poddig, and Fieberg (2018) propose to use the variable selection of Campbell, Hilscher, and Szilagyi (2008) as a benchmark model for Germany, this dissertation is one of the first to test the variable selection of Shumway (2001) on the German market in Model (2). Traditional accounting-based figures measured at book value are used, supplemented by market-driven indicators, for insolvency forecasting. This approach allows more detailed conclusions to be drawn about the significance of hybrid models. A "mixture of pure accounting ratios with market-driven information in Model (2)" (Ledwon and Jäger, 2020, p. 74) shows better performance in the top deciles in the out-of-sample calibration compared to the variable selection of Campbell, Hilscher, and Szilagyi (2008) in Model (3). However, in-sample empirical results highlight the relevance of market-based indicators, as all accounting predictors become statistically insignificant.

Model (4) represents the model output of the stepwise variable selection procedure to obtain the best candidate final regression model. It includes the standard excess past return $EXRET$ and geometrically decreasing weights of $EXRETAVG$ compared to the CDAX in the stepwise variable selection procedure, thus confirming that past excess returns are of great importance for predicting insolvencies. Besides $SIGMA$, $TLMTA$ was chosen as the second measure of solvency, even though it is not statistically significant. This assumes a relationship with one of the other covariates included. With regard to out-of-sample discrimination and calibration, one can conclude that the $iauc$ ratio and best-in-class accuracy rates are satisfactory, even if they do not differ much from the results of Model (2).

Implementing the Cox proportional hazards regression offers a progressive quantitative method to handling unbalanced panel data and delivers a simple and explicit interpretation of hazard ratios. Therefore, the empirical analysis carried out proposes to apply the Cox proportional hazards regression with the AG-CP as a benchmark model for companies listed in Germany. In particular, this dissertation underlines the effect of time-dependent evaluation measures, as constructed data capture a company's time-to-default. Therefore, time-dependent AUC analysis proposed by Chambless and Diao (2006) is used to ensure comparability and account for right-censoring. In comparison to this research, Mertens, Poddig, and Fieberg (2018) have examined insolvencies in the period 1991-2015. Since InsO entered into force in 1999, the earliest year for determining insolvency has been set at 2000. The selected approach is in accordance with the identification of the sample proposed by Hillegeist et al. (2004), which considered statutory changes in the U.S. The selected sample data cover the period from 2000 to 2018. Therefore, "a long time horizon allows to analyze and validate low default rates" (Sobehart, Keenan, and Stein, 2000, p. 8). Thus, a comparatively smaller number of observations does not lead to a downgrading of highlighted empirical results as data adjustment measures aimed to proxy the non-financial entities represented in CDAX, and thus to an increased targeting accuracy, which is underlined in the out-of-sample results of $iauc$.

In addition, this research indicates that the German insolvency forecast "is gradually influenced by the industry to which the company belongs when focusing on discriminatory power" (Ledwon and Jäger, 2020, p. 75). Out-of-sample tests show no universal improvement in model calibration, although the discriminatory power improves and the compared $iauc$ ratios are statistically significant. When the industry grouping is included, an increase in accuracy rates in the top 5 deciles is observed only for the accounting-based Model (1). For Model (3), the decile ranking shown even indicates decreasing calibration results in top deciles. In contrast to the findings of Chava and Jarrow (2004), this dissertation implies that industry grouping brings minor predictive power and no general improvement in accuracy rates if market variables are already incorporated in the PD model.

With regard to the empirical investigation of hazard ratios in the context of the ESUG, the calculated interaction terms could not provide robust and valid in-sample results, mainly due to the low proportion of verified insolvency cases in the context of the ESUG. Since the PH assumption was violated in the $ESUG$ models presented, signs for decreasing hazard rates of the interaction terms $ESUG{:}\,NITA$ and $ESUG{:}\,NIMTA$ should be interpreted with caution.

Further, this research offers a chance for practitioners to discover the application of the extended Cox proportional hazards regression with AG-CP to forecast corporate insolvencies. In particular, the model setup presented can be extended to recurring events in connection with insolvency proceedings and other corporate events of interest. This dissertation can be further used by practitioners to compare the expected insolvency rates with a series of peers, as the analysis carried out considers the industry grouping. Therefore, a company's performance can be validated not only against industry peers but also against external ratings. Finally, the approach chosen provides a framework for the generation of statistics that allow practitioners to assess the predictive power of a model using data that have not been used to fit the model. Practitioners profit from state-of-the-art walk-forward methods according to Sobehart, Keenan, and Stein (2000) because "reparametrized models on a [periodic] basis provide information about economic changes in a realistic and reasonable way" (Ledwon and Jäger, 2020, p. 75).

6.2 LIMITATIONS AND FUTURE OUTLOOK

Although the empirical results presented in this dissertation provide robust findings, some limitations must be taken into account. First and foremost, the rigorously collected sample replicates non-financial entities of the CDAX in Germany between 2000 and 2018. This study is therefore limited to large companies excluding the financial, insurance, and real estate sectors in Germany. The main reason for excluding the respective industries is the high leverage in the financial sector, which probably dilutes the estimation results. Moreover, a majority of the studies carried out focus on non-financial entities, as highlighted in Appendices A-4.1 and A-4.2.

Second, selected explanatory variables are based mainly on Shumway (2001), Chava and Jarrow (2004), and Campbell, Hilscher, and Szilagyi (2008). The stepwise variable selection procedure for Cox's proportional hazards model with forward and backward iteration steps is therefore mainly based on the set of covariates mentioned above.

Third, the development of a PD model for German-listed companies requires a concise definition of corporate failure to ensure the robustness and consistency of the empirical findings. A study by Bahnson and Bartley (1992) confirms that the results of PD models can be influenced by the definition of failure used and emphasizes that future studies should pay particular attention to a clear definition. This empirical study considers the legal definition of the term insolvency and takes into account the inception of InsO in 1999 as well as right-censored data. Therefore, events other than insolvency are also included in the sample, such as M&A, squeeze-outs, and voluntary delistings. As a result, survivorship bias is not primarily present, but the sample is limited in terms of disregard for left-censored data. In addition, reasons to file for insolvency proceedings have been subject to punctual changes in Germany and consequently influence the definition of the event variable. In this regard, the temporary reformulation of the term overindebtedness based on Article 5 of FMStG in 2008 and the recent response measures to the COVID-19 pandemic represented in COVInsAG have been discussed and highlighted in Chapter 3.1. Whereas the former was later embedded in the current statute, the latter would have limited forecast results due to the inherent suspension measures introduced by COVInsAG. According to Hauser (2021), "the swift and decisive central bank action" (Hauser, 2021, p. 3) evolved its role from *Lender of Last Resort* to *Market Maker of Last Resort* which further distorts corporate insolvencies. Consistent with Hauser (2021), Wullweber (2020) elaborates that "central banks have had to step in to prevent large-scale insolvency by providing credit directly to large employers as well as to small and medium-sized businesses to enable them to maintain their business operations and retain their employees" (Wullweber, 2020, pp. 63–64).

Fourth, the misconceptions about the p-value which recently regained scientific attention have been addressed. Issues related to large sample sizes, inappropriate data transformation, and economically counter-intuitive variable selection have been highlighted in Chapter 4.4. while applying literature-based mitigation approaches such as the complementary reporting of confidence intervals and a transparent approach with regard to data collection and adjustment.

Fifth, the discriminatory power of Cox regression models used is evaluated with a recursive calculation of the dynamic AUC for right-censored time-to-event data, as proposed by Chambless and Diao (2006). To distinguish out-of-sample models, the dataset is divided into a training and testing sample with a 70% to 30% data partition, with the company identification remembered. Therefore, a different distribution of data partition may lead to slightly different results in out-of-sample model discrimination.

Sixth, model validation is evaluated using an out-of-sample out-of-time walk-forward analysis to account for data-mining bias. However, further validity studies on the German stock market are required to externally validate empirical findings.

Finally, the inception of the ESUG cannot be fully empirically analyzed, as events in the sample are rare. Wide ranges of confidence intervals and a violation of the PH assumption limit a comprehensive discussion of the effects and changes in hazard ratios.

To date, there is no patent remedy for how best to estimate the probability of default, as Alaminos, Del Castillo, and Fernandez (2016) emphasize. A contemporary trend in the literature on bankruptcy forecasting is the use of hazard models, which, unlike static models, capture the time-to-default of a company and therefore use more observations of company years to explain bankruptcy (Shumway, 2001; Campbell, Hilscher and Szilagyi, 2008; Mertens, Poddig and Fieberg, 2018). The application of an enhanced Cox proportional hazards regression is therefore only a promising attempt to assess corporate insolvency in Germany. Other methodological approaches and research aspects, such as the assessment of impact within the industry and the contagion dynamics could further support the findings of this thesis. Deep immersion in semiparametric Cox proportional hazards regression taking into account the AG-CP for recurring events related to insolvency proceedings and other financial distress seems to be another fruitful area for further academic research.

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APPENDICES

Appendix A-4.1: Selective overview of the relevant PD literature

A comprehensive summary of the most important articles from the literature on bankruptcy forecasting and the corresponding scientific results is presented below. The table is organized according to a methodological approach, which is categorized into the following four parts: (1) discriminant analysis and precursors, (2) logit regression and probit estimation, (3) distance-to-default model, and (4) hazard model.

Author(s)	**Summary**
PANEL 1: Discriminant analysis and precursors	
(Beaver, 1966)	Univariate discriminant study of 30 ratios, which concludes that cash flow to total debt is the best fit single ratio predictor. The research sample consists of 158 listed U.S. companies, 79 of which failed in the years 1954-1964. Each failed company was allocated a non-failed by industry and asset size. The best way to differentiate between failed and non-failed companies was to look at the cash flow/total debt ratio.
(Beaver, 1968)	A subsequent study draws attention to the reaction of investors to earnings announcements. Beaver (1968) argues that changes in the prices of common stocks act as if investors were relying on ratios as predictors of failure.
(Altman, 1968)	Multiple Discriminant Analysis (MDA) from 1946-1965 using the Z-Score of 66 U.S. manufacturing companies, half of which filed for bankruptcy under Chapter VII, resulting in 72% accuracy in predicting bankruptcy two years before the event.
(Deakin, 1972)	Modified MDA approach of 32 U.S. companies, 11 of which failed between 1964-1970. A significant deterioration in the accuracy rate was reported in the 4 to 5 years before the bankruptcy, which is related to the findings of Altman (1968).

Author(s)	Summary
(Altman, Haldeman, and Narayanan, 1977)	Refinement of Altman's (1968) initial contribution to the MDA methodology for predicting corporate failure in the US. The sample is based on 53 U.S. bankrupt companies and 58 non-bankrupt companies. In addition, the originally formulated 5-factor model was expanded to a 7-factor model. The introduced ZETA™ model improves the accuracy rates with over 90% one year before and 70% up to five years before failure. In particular, the cumulative profitability measure, calculated as retained earnings divided by total assets, is the most essential variable – measured univariately and multivariately.
PANEL 2: Logit regression and probit estimation	
(Ohlson, 1980)	Static logistic accounting model from 1970-1976 with over 2,058 U.S. industrial firms, 105 of which filed for bankruptcy under Chapter X or XI using an O-Score with a 96% predictive accuracy of bankruptcy within one year.
(Zmijewski, 1984)	Probit model based on 40 bankrupt and 800 non-bankrupt industrial companies in the U.S. from 1972–1978 to develop the X-score model; Zmijewski (1984) utilized financial ratios that measured firm performance, leverage, and liquidity. The selected ratios are based on the performance achieved in previous studies and used methods are derived based on Ohlson (1980).
PANEL 3: Distance-to-default probability model	
(Black and Scholes, 1973)	Valuation of the equity of the firm in financial distress as a call option with a strike price equal to the face value of the liabilities.
(Merton, 1973)	Merton clarified and extended the Black-Scholes model. Development of the option pricing theory for corporate liabilities.
(Hillegeist et al., 2004)	The market-based approach based on the Black–Scholes–Merton option-pricing model using a hazard model to evaluate Altman (1968) and Ohlson (1980). The collected sample from 1980 to 2000 includes 14,303 companies. Hillegeist et al. (2004) note that the market-based approach provides superior results when compared to the models of Altman (1968) and Ohlson (1980) and accounts for various adjustments such as including the re-estimation of

Author(s)	Summary
	coefficients, making industrial adjustments, and the lagging of the respective scores.
PANEL 4: Hazard models	
(Shumway, 2001)	Shumway (2001) argues that discrete-time hazard models are better suited for forecasting bankruptcy than single-period models. Therefore, a static model is unsuitable for forecasting bankruptcy, as it does not correct for the period at risk and ignores time-variable covariates. In short, a static model uses all available information to produce bankruptcy probability estimates for all firms at any given time. Consequently, two problems associated with the single-period logit approach can be econometrically explained. First, there is a bias in the sample selection resulting from the fact that only one, not randomly selected observation is used per bankrupt company. Second, a failure to model time-varying changes in the underlying or baseline risk of bankruptcy, which leads to cross-sectional dependence of the data. Shumway (2001) shows that these issues lead to biased, inefficient, and generally inconsistent coefficient estimates. All companies that have filed for any type of bankruptcy within 5 years of delisting are considered bankrupt in the respective analysis. The final sample contains 300 U.S. bankruptcies of 3,182 companies between 1962 and 1992. The variable that is of interest in the hazard model is company age. Estimated models are based on independent variables from previous studies, such as the forecast models of Altman (1968) and Zmijewski (1984). In addition, new market-driven independent variables are represented by relative size, past returns, and sigma. The most accurate out-of-sample forecasts are made with a hazard model that uses both market-driven and accounting variables to identify bankrupt companies.

Author(s)	Summary
(Chava and Jarrow, 2004)	Chava and Jarrow (2004) test the forecasting accuracy of bankruptcy hazard rate models for U.S. companies over the period 1962 – 1999, using both yearly and monthly observation intervals. Using an extended bankruptcy database comprising 1,461 bankruptcies, a superior forecasting performance by Shumway (2001) was confirmed compared to Altman (1968) and Zmijewski (1984). Moreover, industry effects in hazard rate estimation are investigated. It has been shown that industry groupings significantly influence both the intercept and slope coefficients in the forecasting equations. Finally, the hazard rate models for financial firms are isolated and extended to include monthly observation intervals since most of the existing literature uses only annual observations due to data limitations. Chava and Jarrow (2004) improve bankruptcy prediction when they use monthly observation intervals. Finally, with respect to publicly available information related to market efficiency, Chava and Jarrow (2004) conclude that accounting variables add little predictive power when market variables are already included in the bankruptcy model.
(Beaver, McNichols, and Rhie, 2005)	Using a hazard model, Beaver, McNichols, and Rhie (2005) examine secular changes in the ability of financial statement data to predict bankruptcy from 1962-2002. The respective sample consists of U.S.-listed companies from 1962 to 2002, including 544 bankrupt non-financial firms as well as 4,237 non-bankrupt entities A parsimonious three-variable model provides a significant explanatory power over the entire period, with only a slight deterioration in predictive power from the first to the second period. First, return on total assets measures takes into account profitability, which has been shown to be a crucial factor in previous empirical contributions. The second factor refers to Beaver's (1966) best single predictor cash-flow to total debt, which in this analysis is defined as net income to total liabilities. The third element is represented by the leverage ratio of total liabilities in relation to total assets. A major difference to the approach of Shumway (2001) is that the identification and implementation of accounting-based variables have predictive

Author(s)	Summary
	power. Empirical results from Beaver, McNichols, and Rhie (2005) show that the models maintain the robustness of the predictive power over time while observing a slight decline in the predictive ability of accounting-based variables, which is offset by an improvement in the incremental predictive ability of market-related variables.
(Campbell, Hilscher, and Szilagyi, 2008)	Campbell, Hilscher, and Szilagyi (2008) use a hazard model methodology developed by Shumway (2001) and applied by Chava and Jarrow (2004). 800 U.S. bankruptcies in the period from 1963 to 1998 are tested against various specifications. The most appropriate model obtaining includes both market-based and accounting data. Modifying net income and leverage by the market value of assets instead of the book value and adding further delays in stock returns and net income improves the explanatory power of the model. Additional variables, such as corporate cash holdings, the market-to-book ratio, and a price per share of a company contribute to the explanatory power. In connection with the subsequent part of the paper, a measure of distance-to-default is introduced, which gives relatively little explanatory power to the reduced form variables already included.
(Wu, Gaunt, and Gray, 2010)	Wu, Gaunt, and Gray (2010) compare and evaluate the performance of five key models represented by Altman (1968), Ohlson (1980), Zmijewski (1984), Shumway (2001), and (Hillegeist et al., 2004). Furthermore, a new model is being constructed that contains key variables from each of the five models. The sample covers the period from 1980 to 2006 and includes 887 U.S. bankruptcies and 49,724 non-bankrupt company years. Wu, Gaunt, and Gray (2010) add a new variable that indicates the degree of diversification within the company while indicating the number of business segments in a company. Based on the model-fit criteria, the MDA model of Altman (1968) performs poorly compared to the static approach of Ohlson (1980) and Zmijewski (1984). The model of Shumway (2001) surpasses this, as previous academic research confirms. The distance-to-default model proposed by Hillegeist et al. (2004) does

Author(s)	**Summary**
	not surpass the hazard model. A new hazard model based on the covariates with the highest information content is capable of achieving the highest predictive power.
(Bauer and Agarwal, 2014)	Bauer and Agarwal (2014) extensively test the performance of hazard models for a sample of the most important companies listed in the U.K. between 1979 and 2009 based on Shumway (2001) against the traditional accounting-based approach by Altman (1968) or the contingent claims approach by Hillegeist et al. (2004). The models are evaluated according to the criteria of accuracy, information content, and economic value, and show that the hazard models based on Shumway (2001) give the best results in all three evaluation criteria and represent the most suitable model for the U.K. market.

[Source: Author's representation]

Appendix A-4.2: Selective literature on German PD models

In the following, a comprehensive summary of the most important scientific contributions in German literature is presented together with the respective results. Panel 5 provides a chronological overview of MDA, logit methodology, support vector machine approach as well as hazard models.

Author(s)	**Summary**
PANEL 5: German PD literature	
(Perlitz, 1973)	Perlitz (1973) carries out one of the first MDA analyses for companies listed in Germany. His sample consists of 90 listed companies that were analyzed between 1966-1968. A total of 6 variables are included in his final model, resulting in an accuracy rate of over 90%.
(Baetge, Huß, and Niehaus, 1987)	Baetge, Huß, and Niehaus (1988) use MDA for German companies with a set of 3 identified variables that capture the capital structure, profitability, and solvency of a company. The main objective of the study carried out was to achieve at least 80% accuracy in predicting financially distressed companies three years before the event.
(Schuhmacher, 2006)	Schuhmacher (2006) develops a rating for German SMEs. A comparative study of over 1,997 German SMEs between 1997 and 2003 confirms that a hazard model outperforms the static logit methodology for predicting defaults.
(Behr and Güttler, 2007)	Behr and Güttler (2007) construct a logit-scoring model from 1992 to 2002 to predict the probability of default for German SMEs using a unique data set on SME loans in Germany in order to promote knowledge about their default risk and to apply the adequate cost of debt.
(Härdle et al., 2009)	Härdle et al. (2009) compare the performance of linear discriminant analysis, logit models, and support vector machines and conclude that support vector machines should ultimately not be seen as a replacement for traditional methods but rather as a complementary approach to either the logit model or discriminant analysis. The database consists of 20,000 financially solvent and 1000 insolvent German companies, which were observed once in the period from 1997 to 2002.

(Elsas and Mielert, 2010)	Elsas and Mielert (2010) provide evidence for the discriminatory effect of the DD Model on the German stock market with a mean out-of-sample AUC of 85% for 158 non-financial German insolvencies between the years 2000 to 2009. Respective empirical results are further supplemented by a case study on Arcandor AG, validating high default rates in comparison to european peers.
(Mertens, Poddig, and Fieberg, 2018)	Mertens, Poddig, and Fieberg (2018) test various default risk models using manually retrieved data on German corporate defaults from TDS. In this context, the authors evaluate the structural Merton distance-to-default (DD), Altman's (1968) Z-score as well as the hazard model of Campbell, Hilscher, and Szilagyi (2008). A set of performance assessment tools, including ROC analysis, model calibration tests, and finally a loan market simulation, are applied, indicating that the Campbell, Hilscher, and Szilagyi (2008) model outperforms the other models. Even though the performance evaluation shows that the failure score does provide superior results as compared to U.S. data, the authors suggest it as a benchmark default risk model. Furthermore, the authors underpin several pitfalls associated with the application of Altman's (1968) Z-score and the DD approach. Mertens, Poddig, and Fieberg (2018) claim that the former has a very weak discriminatory power, and the latter is severely miscalibrated.

[Source: Author's representation]

Appendix A-4.3: Categorization of potential explanatory covariates

This table shows potential explanatory covariates that were extracted from the comprehensive literature review in Chapter 4.1 and are to be tested for their eligibility. Each represented variable is supplemented by its source, category, and, if available, by the sign of its coefficient. All abbreviations are listed accordingly in the table of symbols.

No.	Variables	Category	Signs	Literature
Solvency				
A1	CF/D	*Accounting*	-	A; G
A2	ME/TL	*Accounting*	+/-	B; H; I; N; O
A3	TL/TA	*Accounting*	+	E; F; H; I; J; K; L; N
A4	CL/CA	*Accounting*	+	E
A5	$OENEG$	*Accounting*	-	E
A6	FU/TL	*Accounting*	-	E
A7	E/TA	*Accounting*	n/a	G
A8	$SIGMA$	*Market*	+	H; I; J; K; M; N; O
A9	ICR	*Accounting*	n/a	D
A10	$5yr.ME/TC$	*Accounting*	n/a	D
A11	NI/TL	*Accounting*	-	J
A12	TL/MTA	*Market*	+/-	K; M; O
A13	E/TA	*Accounting*	n/a	C; L
A14	$EBIT/CL$	*Accounting*	n/a	C
Liquidity				
B1	WC/TA	*Accounting*	+/-	B; E; H; I; M; N; O
B2	*CF/TA*	*Accounting*		C; G
B3	*CA/CL*	*Accounting*	-	F; D; H, I
B4	*CASH/MTA*	*Market*	-	K; O
B5	*CASH/TA*	*Accounting*	n/a	L
Profitability				
C1	$EBIT/TA$	*Accounting*	+/-	B; C; D; H; I; J; L; M; N; O
C2	$SE\ of\ EBIT/TA$	*Accounting*	n/a	D

No.	Variables	Category	Signs	Literature
C3	$Sales/TA$	*Accounting*	+/-	B; H; I; N; O
C4	RE/TA	*Accounting*	+/-	B; D; H; I; N; O
C5	NI/TA	*Accounting*	-	E; F; H; I; K; N
C6	$INTWO$	*Accounting*	+	E
C7	$CHIN$	*Accounting*	-	E; M
C8	$EXRETAVG$	*Market*	-	H; I; J; K; M; N; O
C9	$RSIZE$	*Market*	+/-	H; I; J, K; N; O
C10	NI/MTA	*Market*	+/-	K; O
C11	OI/TA	*Accounting*	n/a	L
C12	OI/S	*Accounting*	n/a	L
C13	$EBITDA/TA$	*Accounting*	n/a	L
C14	$EBIT/S$	*Accounting*	n/a	C; L
C15	NI/S	*Accounting*	n/a	L
Other variables				
D1	$SIZE$	*Macro*	-	E
D2	$Norm.TA$	*Accounting*	n/a	D
D3	MB	*Control*	+/-	K; O
D4	$PRICE$	*Market*	-	K; M; O
D5	TA/S	*Accounting*	n/a	L
D6	INV/S	*Accounting*	n/a	L
D7	AR/S	*Accounting*	n/a	L
D8	AP/S	*Accounting*	n/a	L
D9	$IDINV$	*Accounting*	n/a	L
D10	Segment	*Macro*	-	M
D11	$Payout/S$	*Accounting*	n/a	C

Notes: **A**: Beaver (1966); **B**: Altman (1968); **C**: Perlitz (1973); **D**: Altman, Haldeman, and Narayanan (1977); **E**: Ohlson (1980); **F**: Zmijewski (1984); **G**: Baetge, Huß, and Niehaus (1987); **H**: Shumway (2001); **I**: Chava and Jarrow (2004); **J**: Beaver, McNichols, and Rhie (2005); **K**: Campbell, Hilscher, and Szilagyi (2008); **L**: Härdle et al. (2009); **M**: Wu, Gaunt, and Gray (2010); **N**: Bauer and Agarwal (2014); **O**: Mertens, Poddig, and Fieberg (2018) [Source: Author's representation]

Appendix A-5.1: Kaplan-Meier survival curve estimation

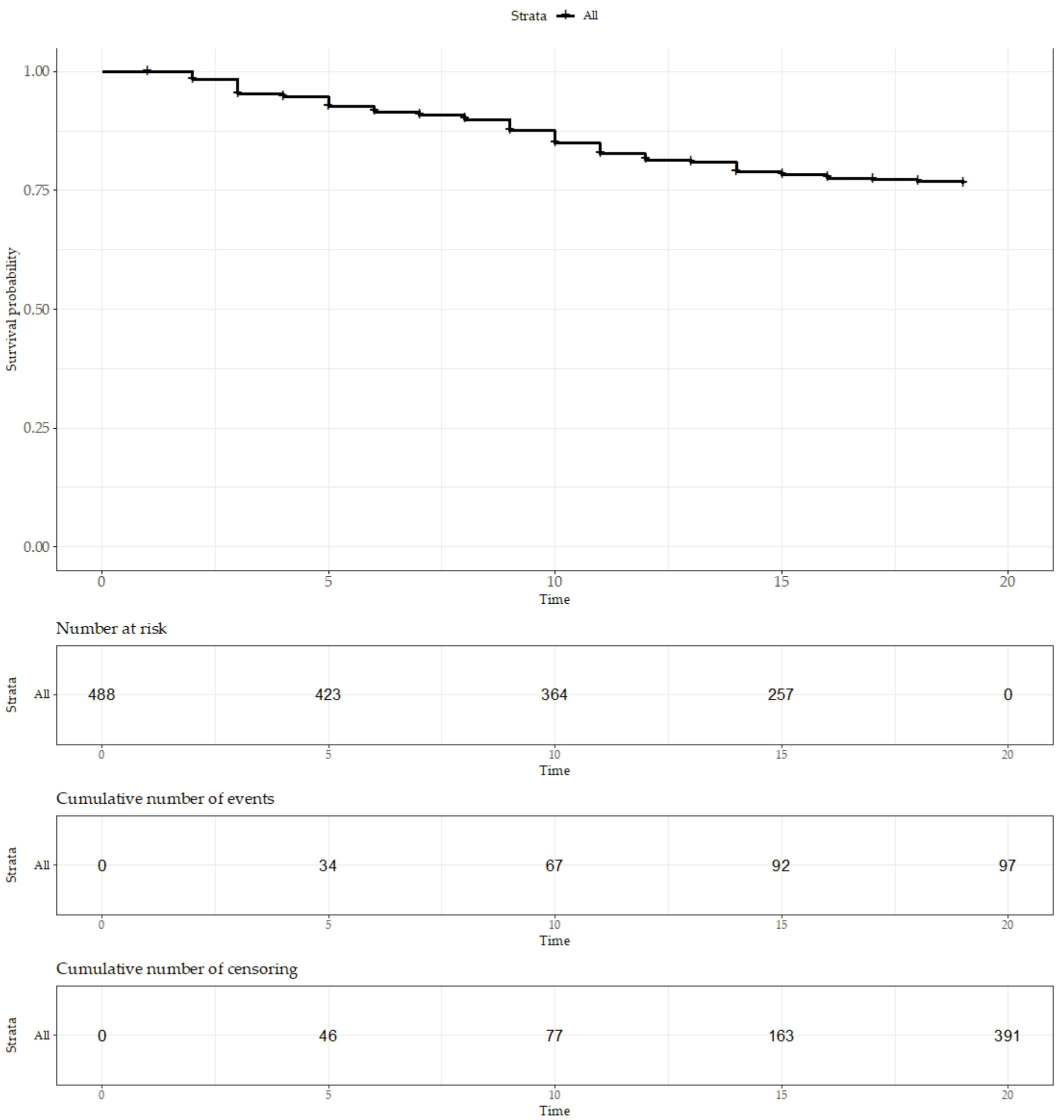
Non-parametric Kaplan-Meier estimator with 95% confidence intervals to underpin descriptive purposes before a regression model with regressors is implemented, where: $\boldsymbol{t_j}$ = Time interval; $\boldsymbol{n_j}$ = Number at risk; $\boldsymbol{d_j}$ = Number of defaults; $\boldsymbol{c_j}$ = Number of censored observations; $\boldsymbol{\hat{S}(t_j)}$= Survival function; $\boldsymbol{SE}$= Standard error; $\boldsymbol{uI}$ = upper 95% Confidence interval; $\boldsymbol{lI}$ = lower 95% confidence interval

t_j	n_j	d_j	c_j	$\hat{S}(t_j)$	SE	uI	lI
1	488	0	10	1.00	0.00	1.00	1.00
2	478	8	9	0.98	0.01	0.97	1.00
3	461	14	8	0.95	0.01	0.94	0.97
4	439	3	13	0.95	0.01	0.93	0.97
5	423	9	6	0.93	0.01	0.90	0.95
6	408	5	5	0.92	0.01	0.89	0.94
7	398	3	4	0.91	0.01	0.88	0.94
8	391	4	4	0.90	0.01	0.87	0.93
9	383	10	9	0.88	0.02	0.85	0.91
10	364	11	9	0.85	0.02	0.82	0.88
11	344	9	8	0.83	0.02	0.79	0.86
12	327	5	18	0.81	0.02	0.78	0.85
13	304	2	23	0.81	0.02	0.77	0.85
14	279	7	15	0.79	0.02	0.75	0.83
15	257	2	22	0.78	0.02	0.74	0.82
16	233	2	8	0.78	0.02	0.74	0.82
17	223	1	4	0.77	0.02	0.73	0.81
18	218	1	13	0.77	0.02	0.73	0.81
19	204	1	203	0.77	0.02	0.72	0.81

[Source: Author’s representation]

Appendix A-5.2: Kaplan-Meier estimator with complementary data

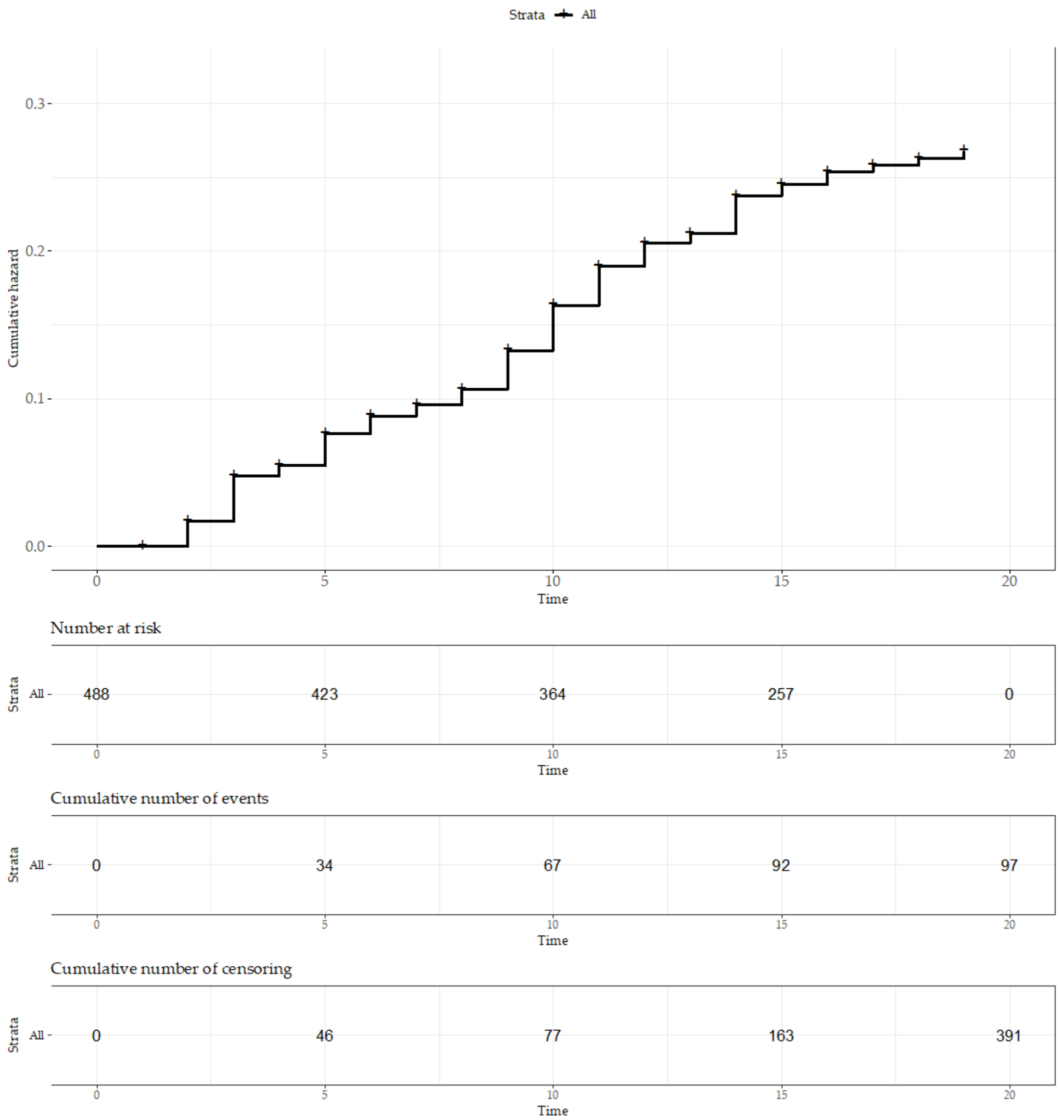
Survival curve with absolute risk table, cumulative events, and cumulative censoring



[Source: Author's representation]

Appendix A-5.3: Nelson-Aalen estimator with supplementary data

Cumulative Hazard including absolute risk table, cumulative events, and cumulative censoring

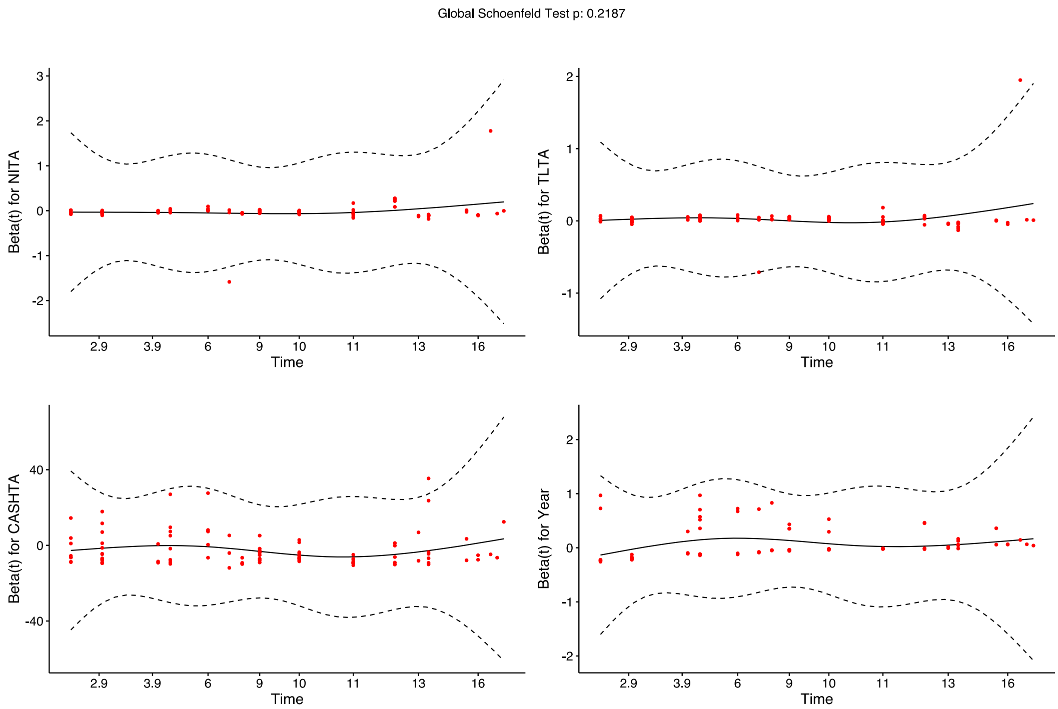


[Source: Author's representation]

Appendix A-5.4: Graphical diagnostics of the Schoenfeld individual test

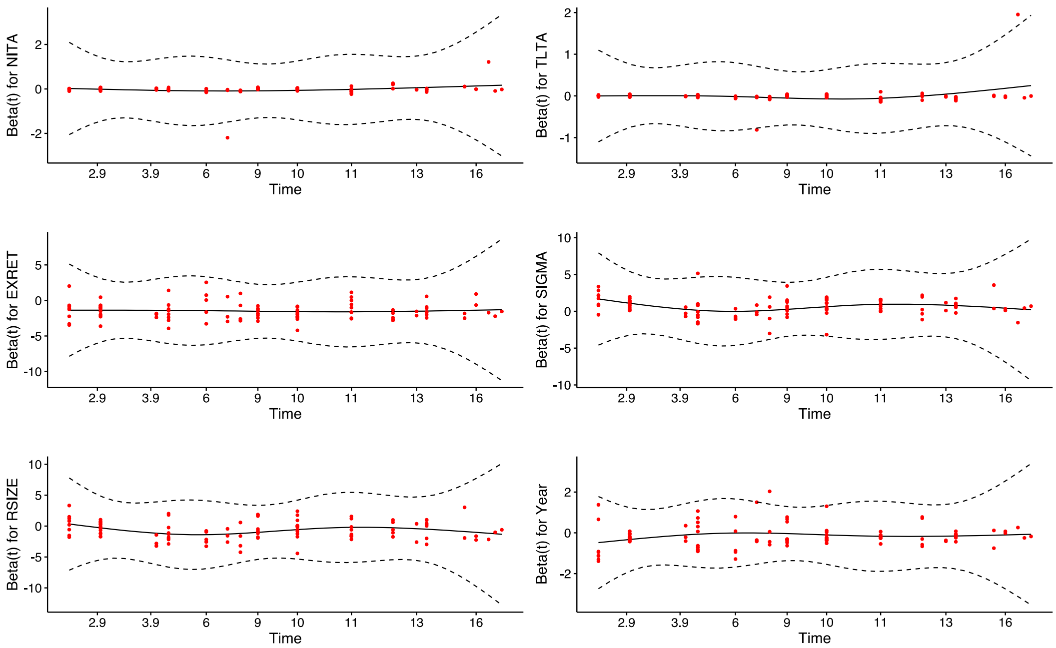
Schoenfeld individual test for Models (1) – (4) and Models (1) IND – (4) IND to check for non-random patterns against time and thus for a violation of the PH. Solid lines show smoothing splines. Dotted lines represent a ± 2-standard error confidence band.

Schoenfeld individual test Model (1)



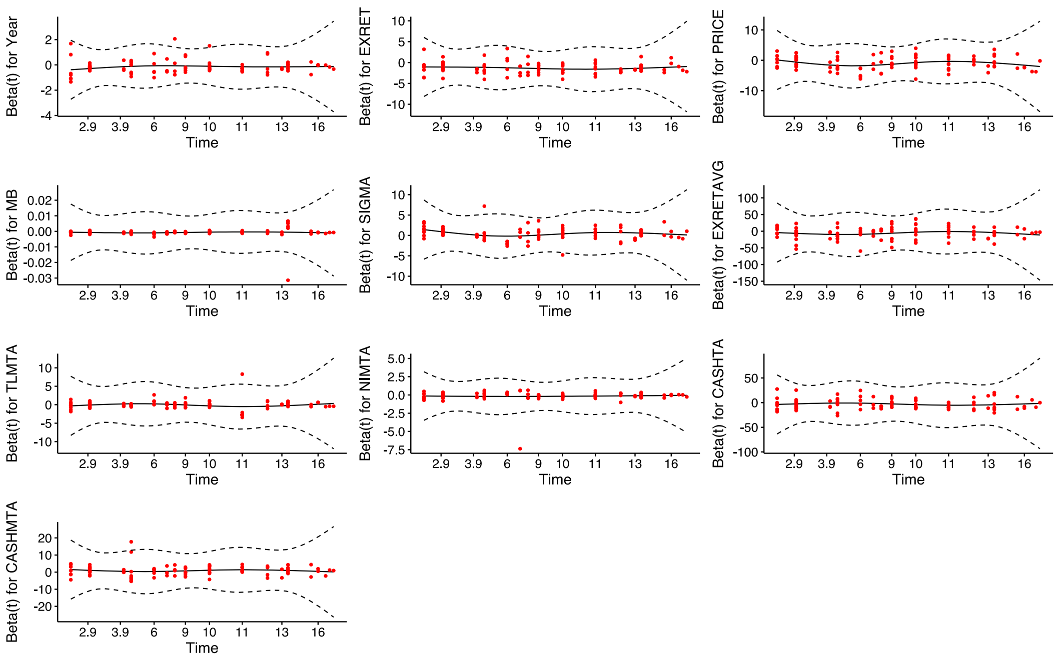
Schoenfeld individual test Model (2)

Global Schoenfeld Test p: 0.3034



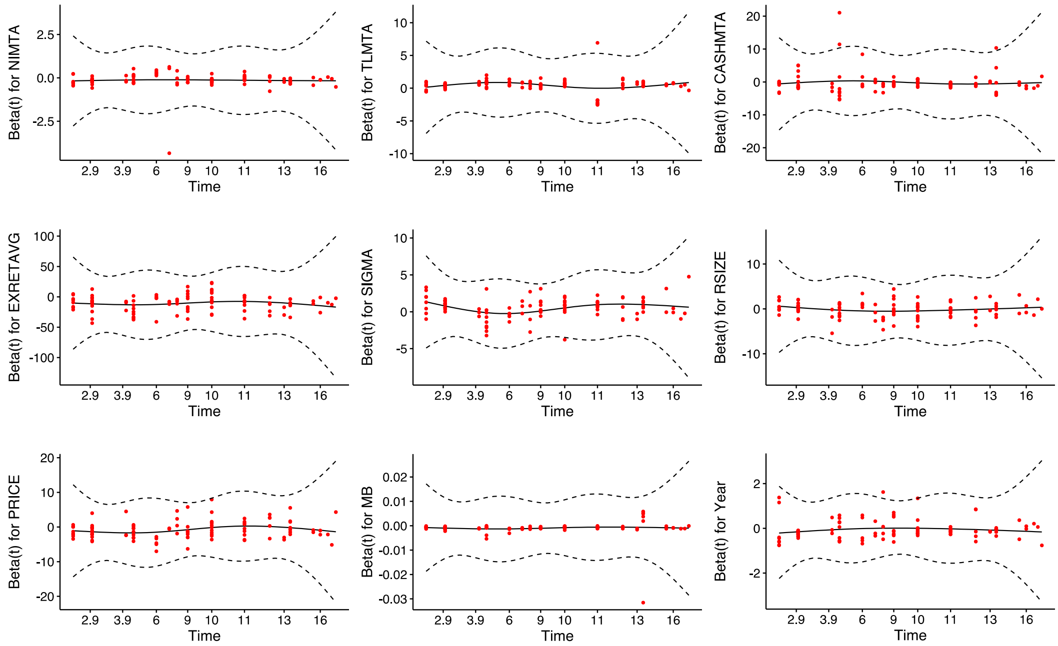
Schoenfeld individual test Model (3)

Global Schoenfeld Test p: 0.7598



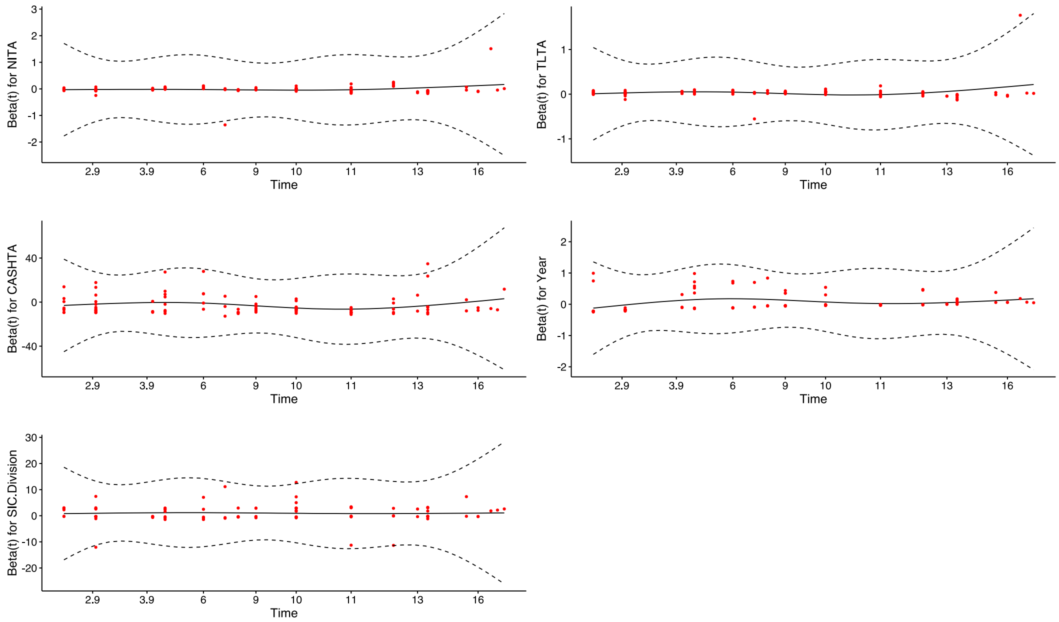
Schoenfeld individual test Model (4)

Global Schoenfeld Test p: 0.4356



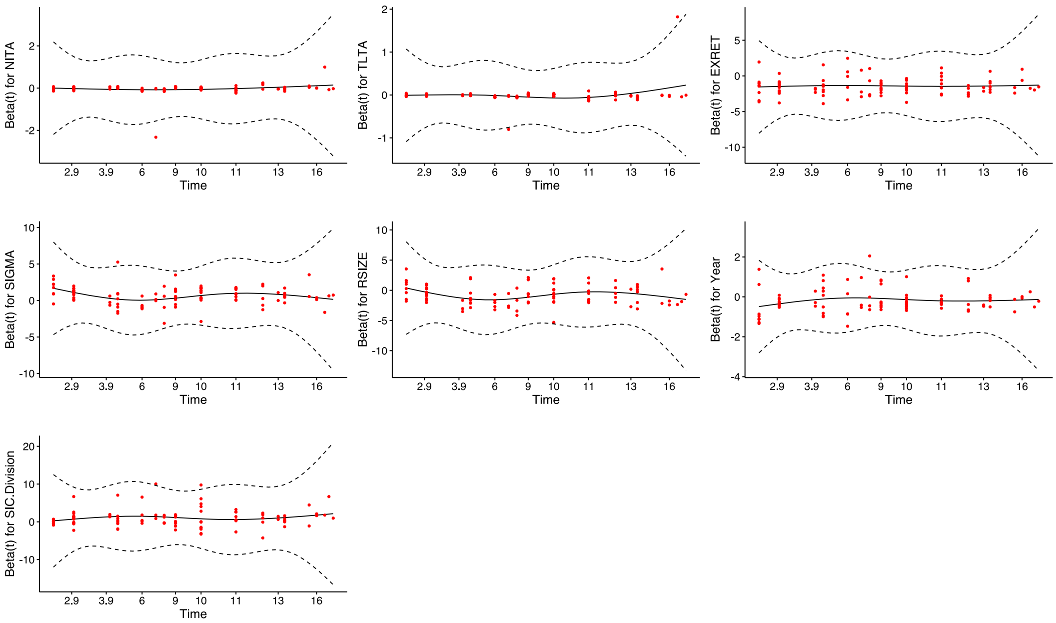
Schoenfeld individual test Model (1) IND

Global Schoenfeld Test p: 0.3633



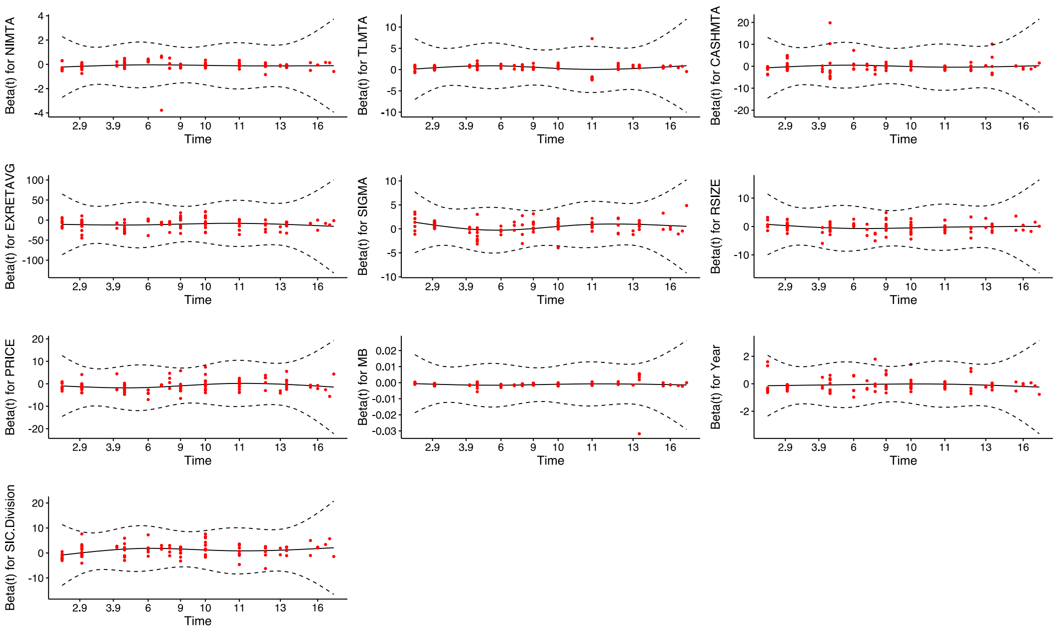
Schoenfeld individual test Model (2) *IND*

Global Schoenfeld Test p: 0.8116

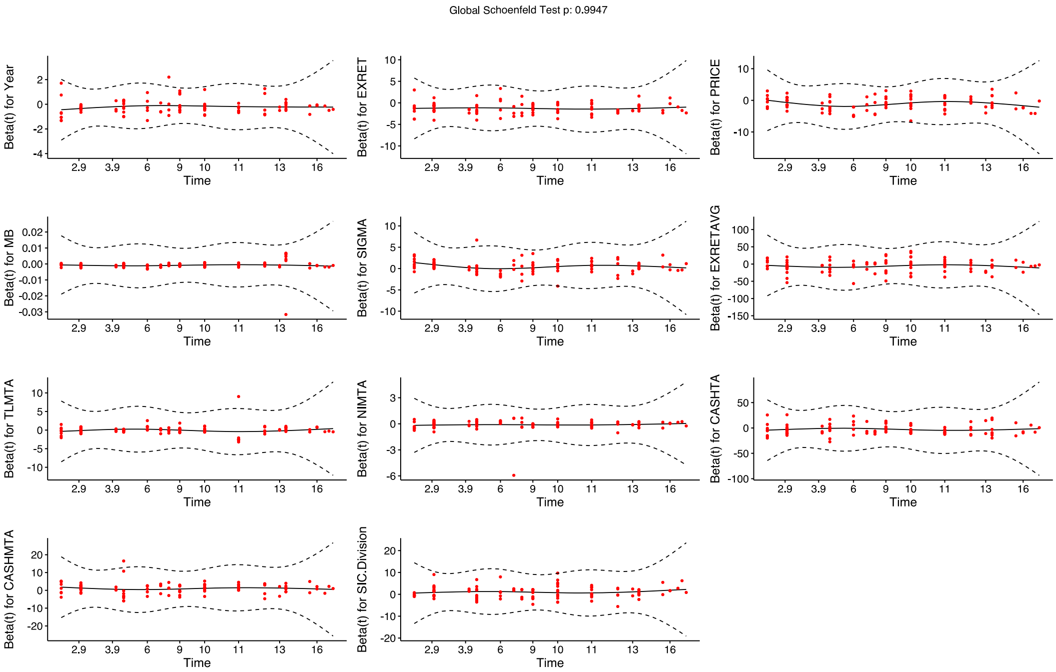


Schoenfeld individual test Model (3) *IND*

Global Schoenfeld Test p: 0.3363



Schoenfeld individual test Model (4) IND

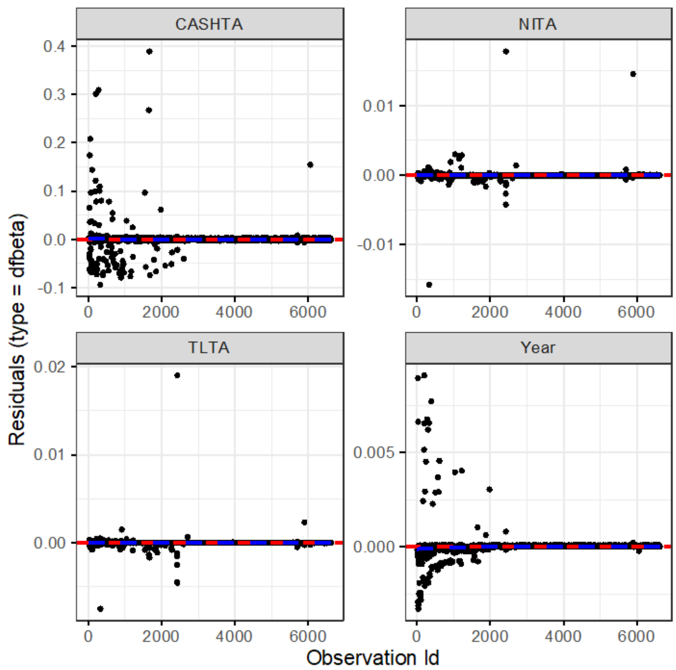


[Source: Author’s representation]

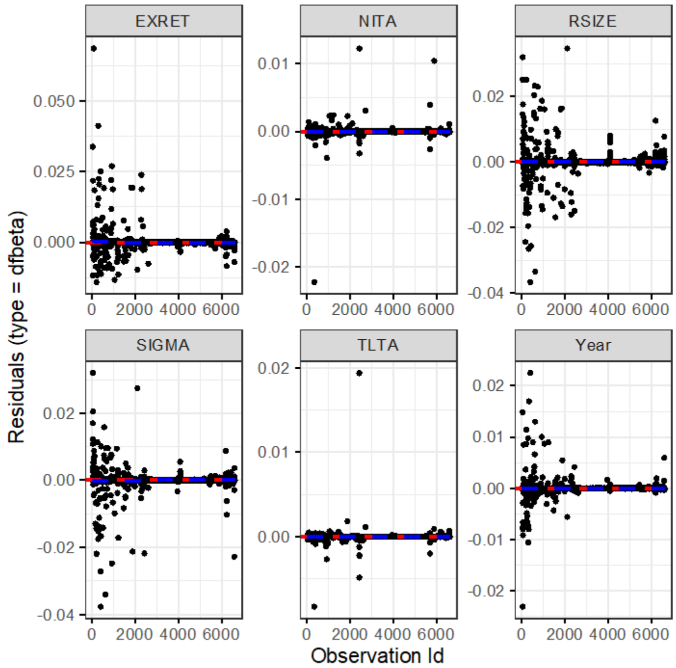
Appendix A-5.5: Graphical diagnostics of dfbeta index plots

Index plots of dfbeta for Model (1) – Model (4) and Model (1) IND – Model (4) IND are presented to identify outliers and influential data points. Specifying the argument type=dfbeta in R illustrates the estimated changes in the regression coefficients when deleting each case in turn. The dashed blue line represents the local average for deviating residuals. The dashed red line indicates a horizontal line to highlight the Y= 0 level.

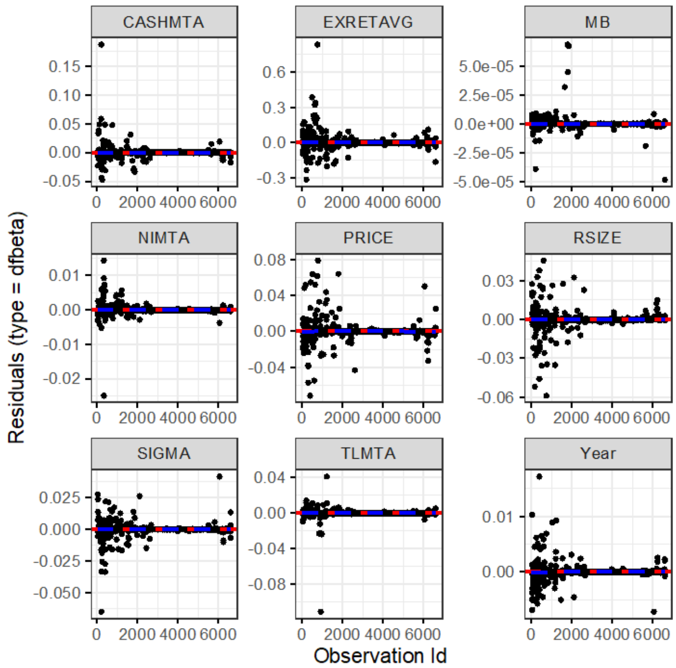
Index plot dfbeta Model (1)



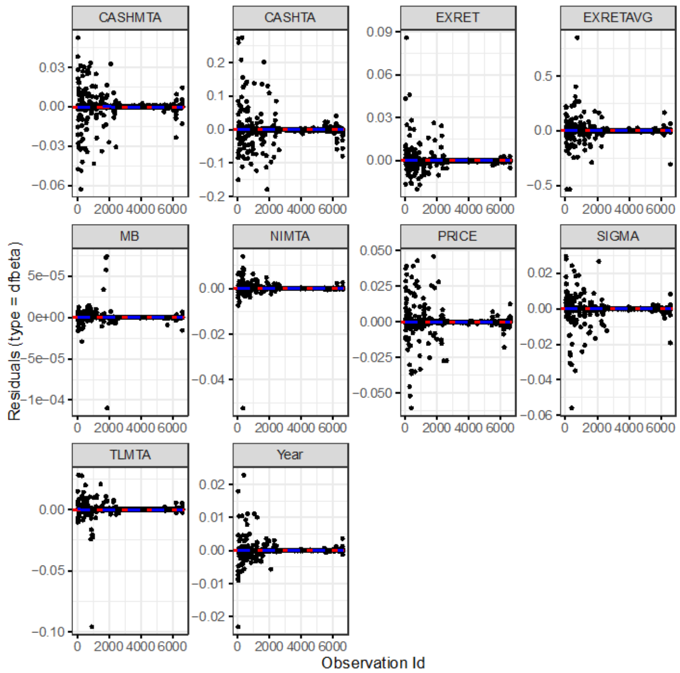
Index plot dfbeta Model (2)



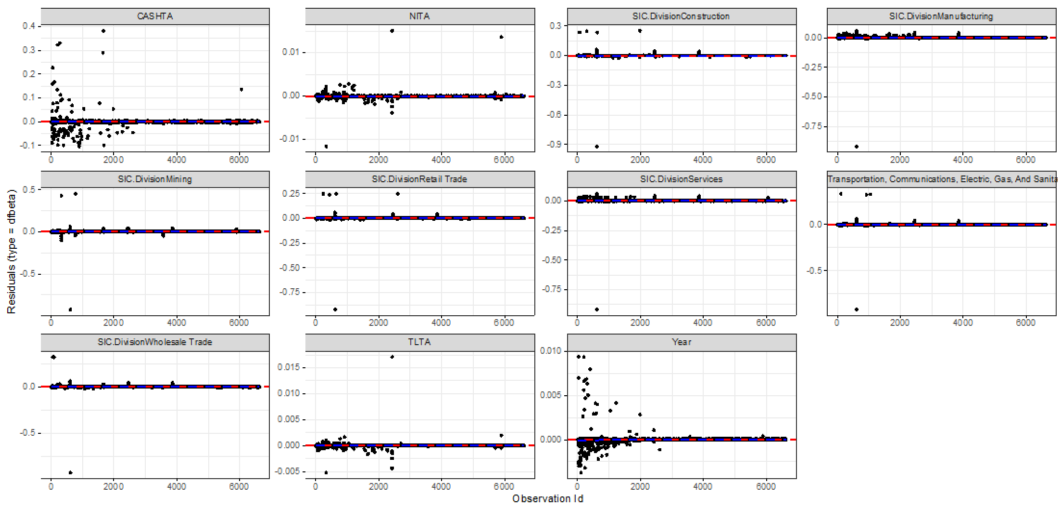
Index plot dfbeta Model (3)



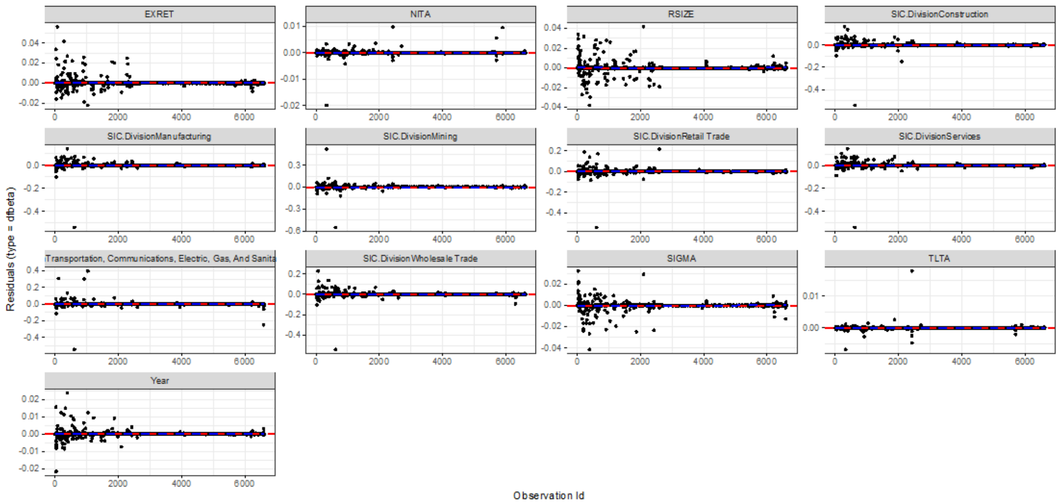
Index plot dfbeta Model (4)



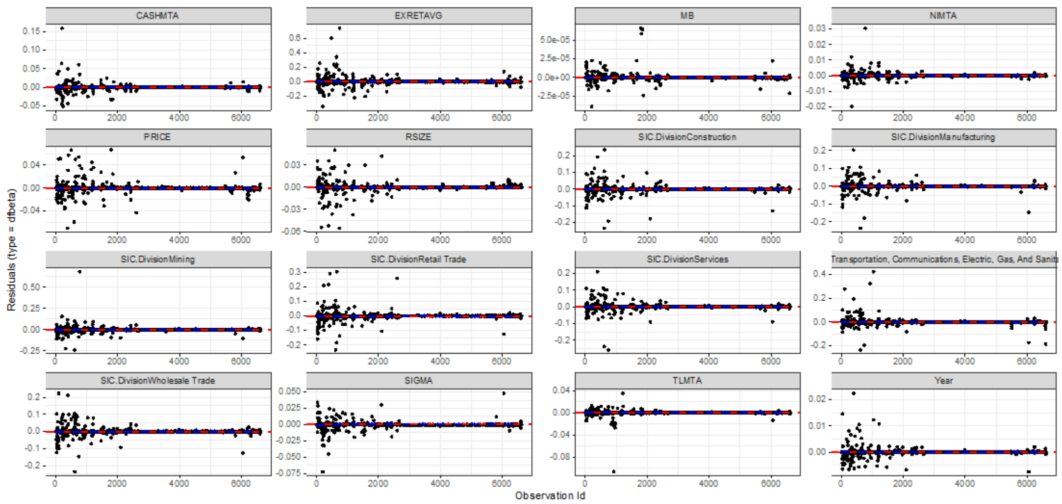
Index plot dfbeta Model (1) *IND*



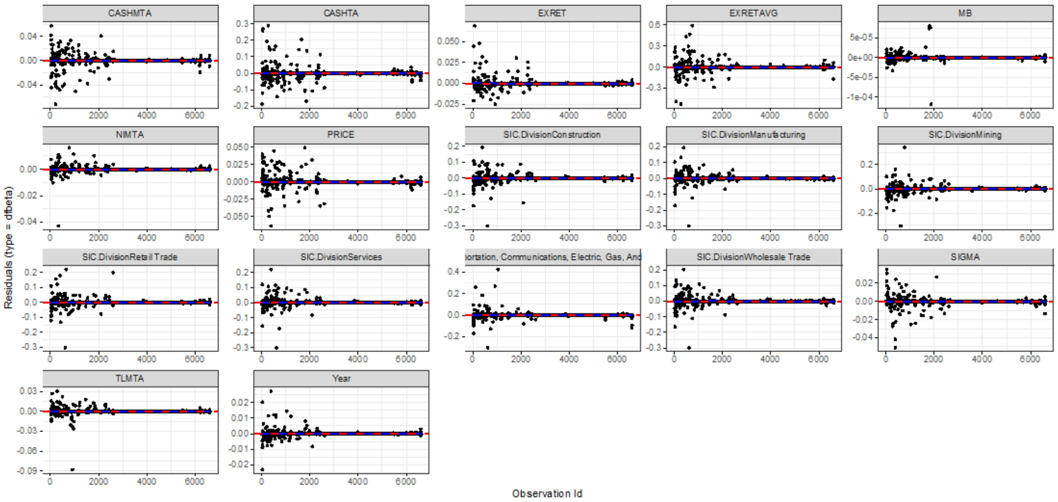
Index plot dfbeta Model (2) IND



Index plot dfbeta Model (3) IND



Index plot dfbeta Model (4) IND

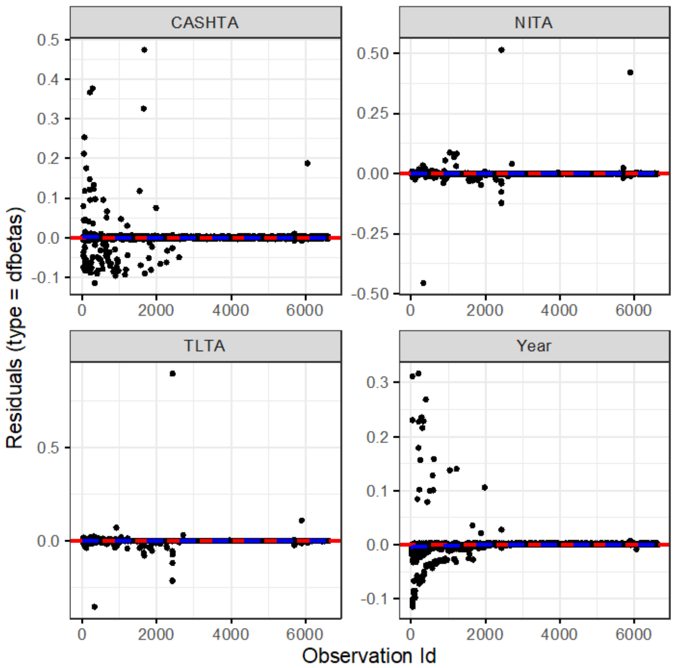


[Source: Author's representation]

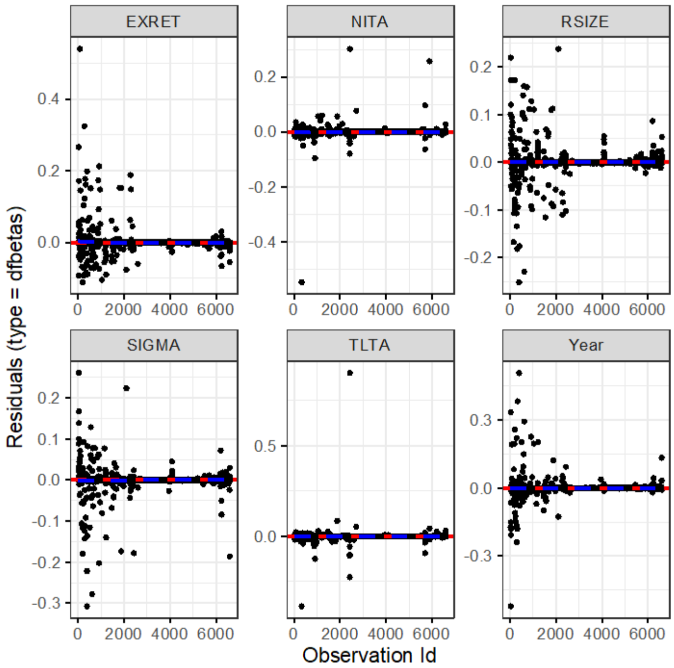
Appendix A-5.6: Graphical diagnostics of dfbetas index plots

Index plots of dfbetas for Models (1) – (4) and Models (1) IND – (4) IND are presented to identify outliers and influential data points. Specifying the argument type=dfbetas in R illustrates the estimated changes in the coefficients divided by their standard errors. The dashed blue line represents the local average for deviating residuals. The dashed red line indicates a horizontal line to highlight the Y= 0 level.

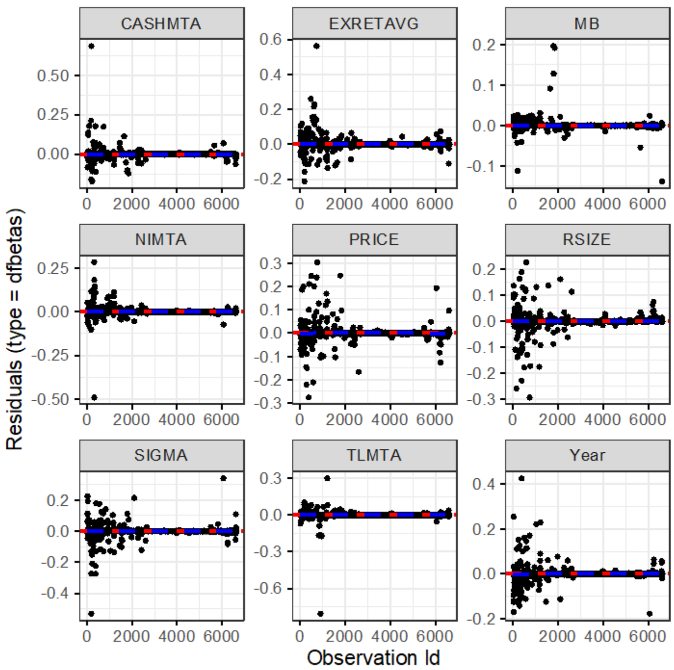
Index plot dfbetas Model (1)



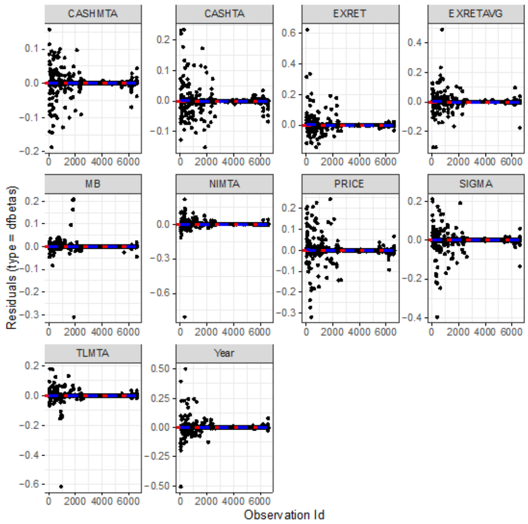
Index plot dfbetas Model (2)



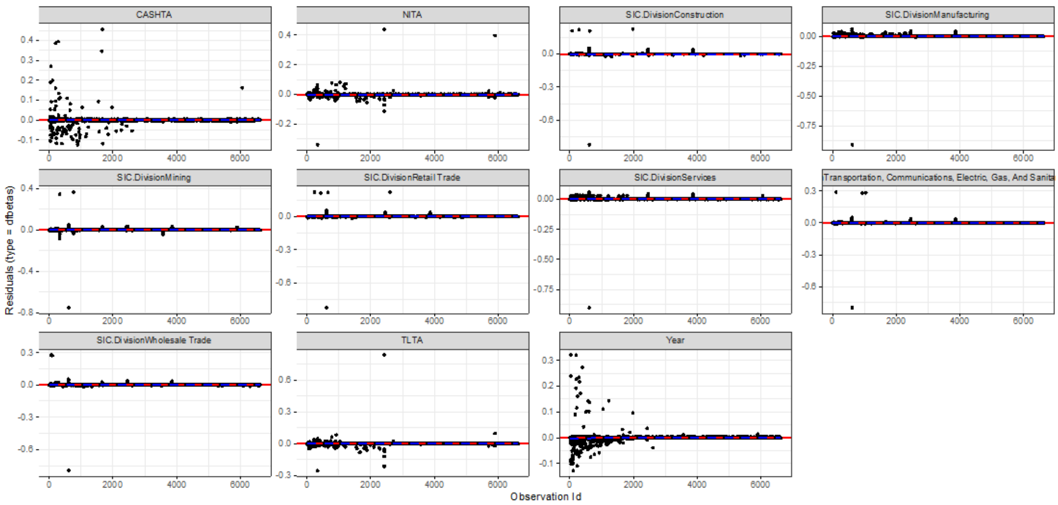
Index plot dfbetas Model (3)



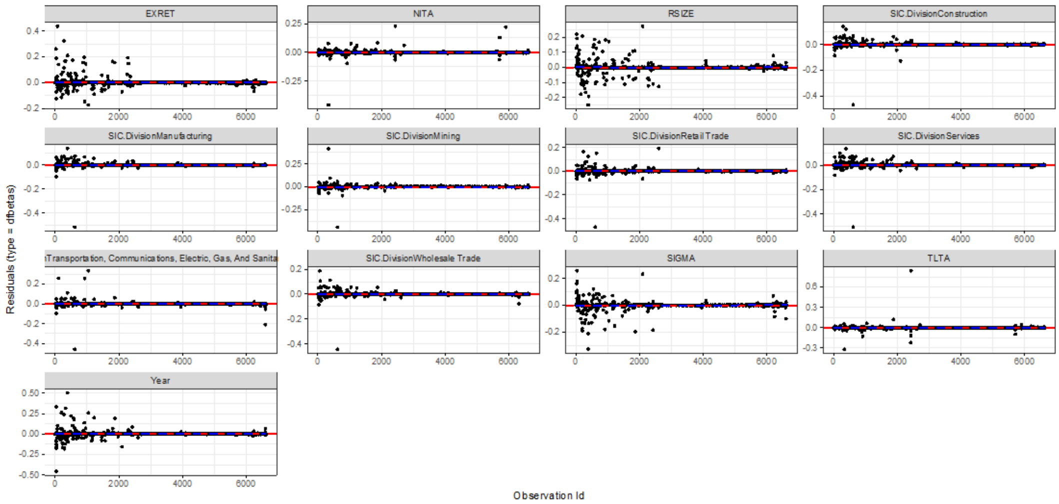
Index plot dfbetas Model (4)



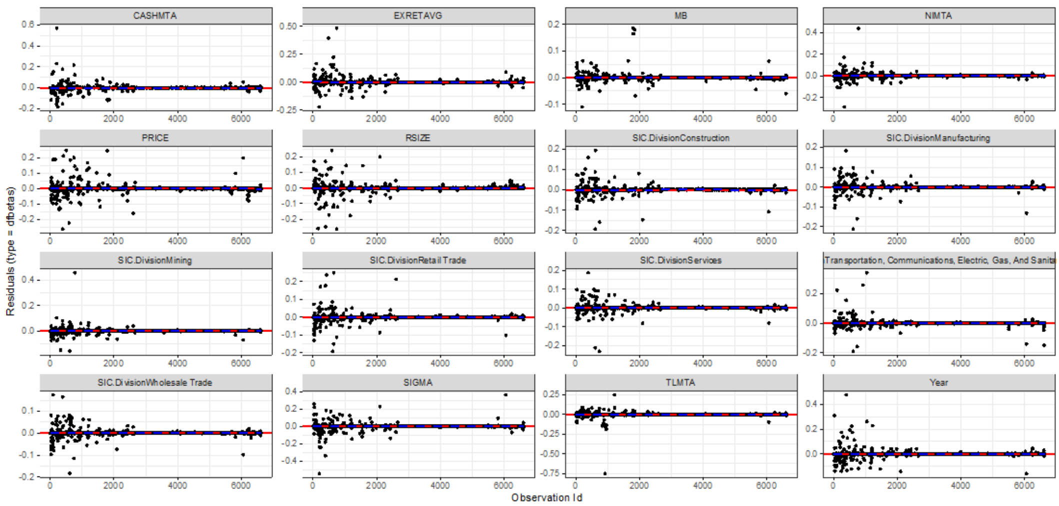
Index plot dfbetas Model (1) IND



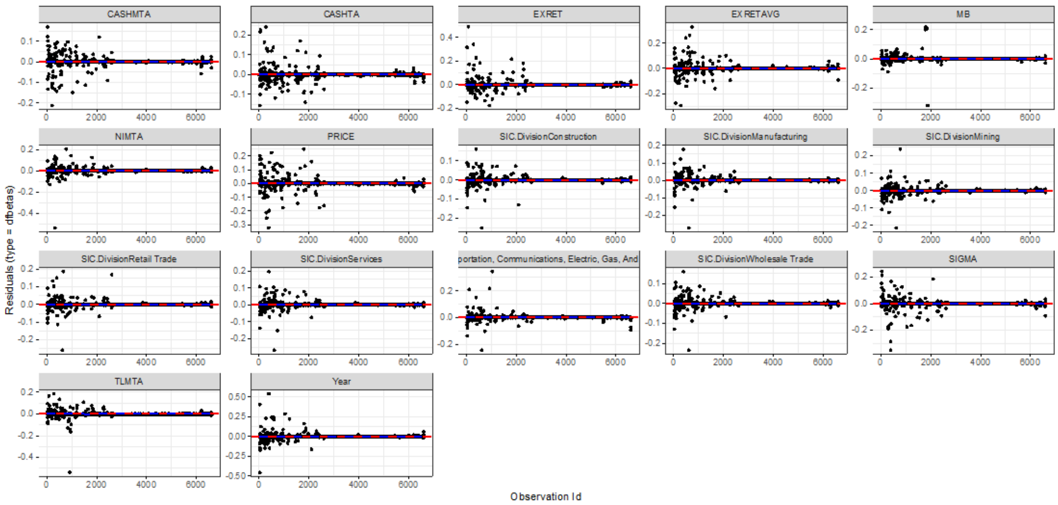
Index plot dfbetas Model (2) IND



Index plot dfbetas Model (3) IND



Index plot dfbetas Model (4) IND

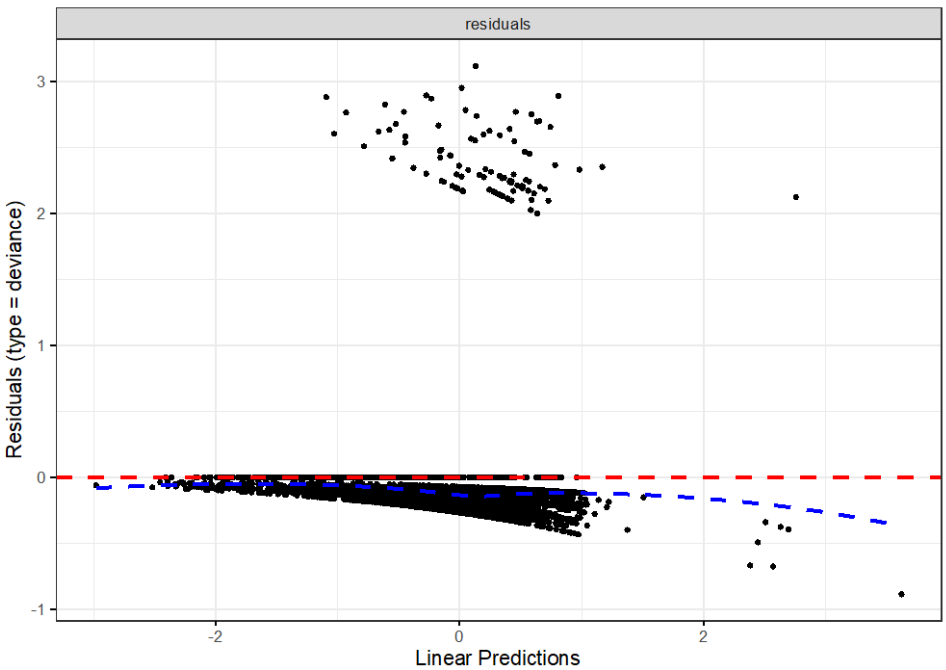


[Source: Author's representation]

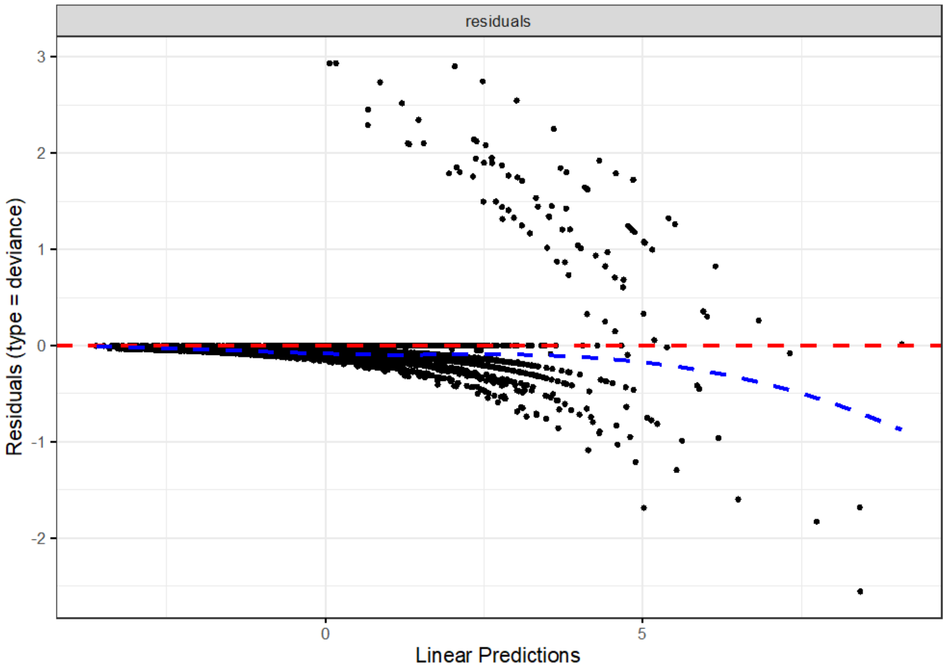
Appendix A-5.7: Graphical diagnostics of deviance residuals

Index plots of deviance residuals for Models (1) – (4) and Models (1) IND – (4) IND are presented to identify outliers and influential data points. Specifying the argument type=deviance in R illustrates the symmetric transformation of the Martingale residuals. The dashed blue line represents the local average for deviating residuals. The dashed red line indicates a horizontal line to highlight the Y= 0 level.

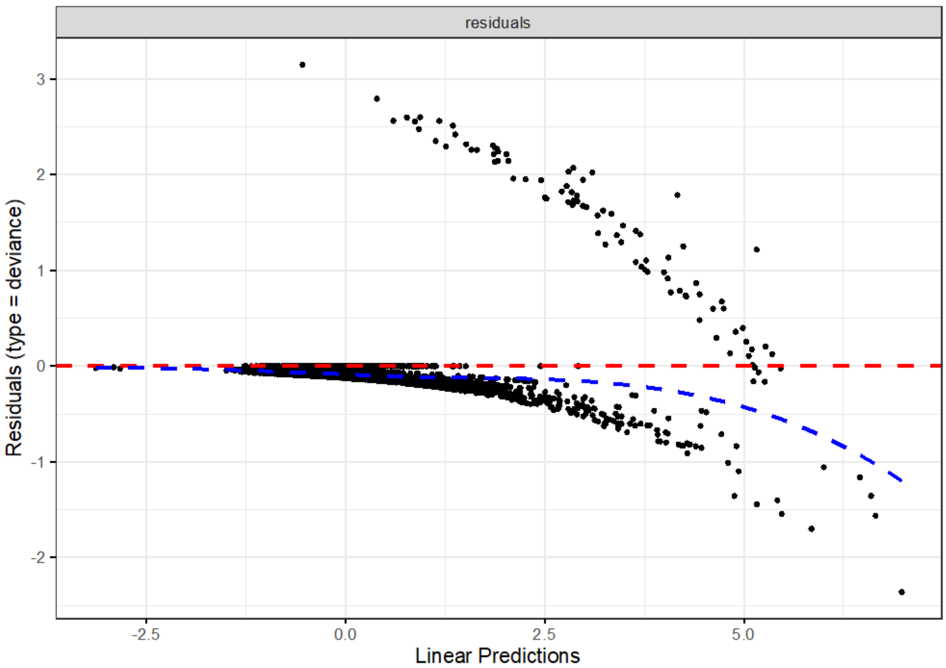
Index plots deviance residuals Model (1)



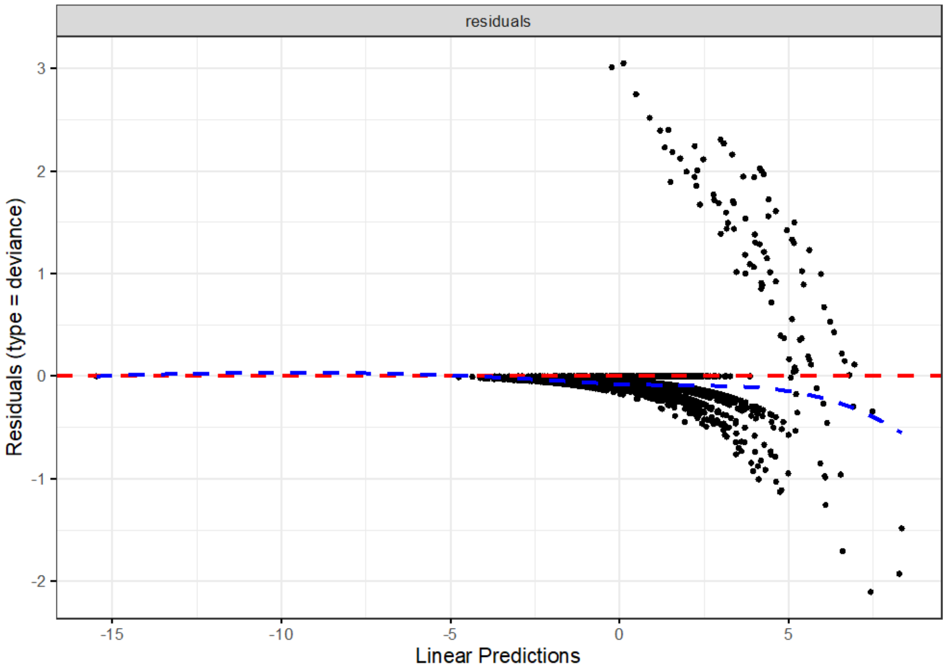
Index plots deviance residuals Model (2)



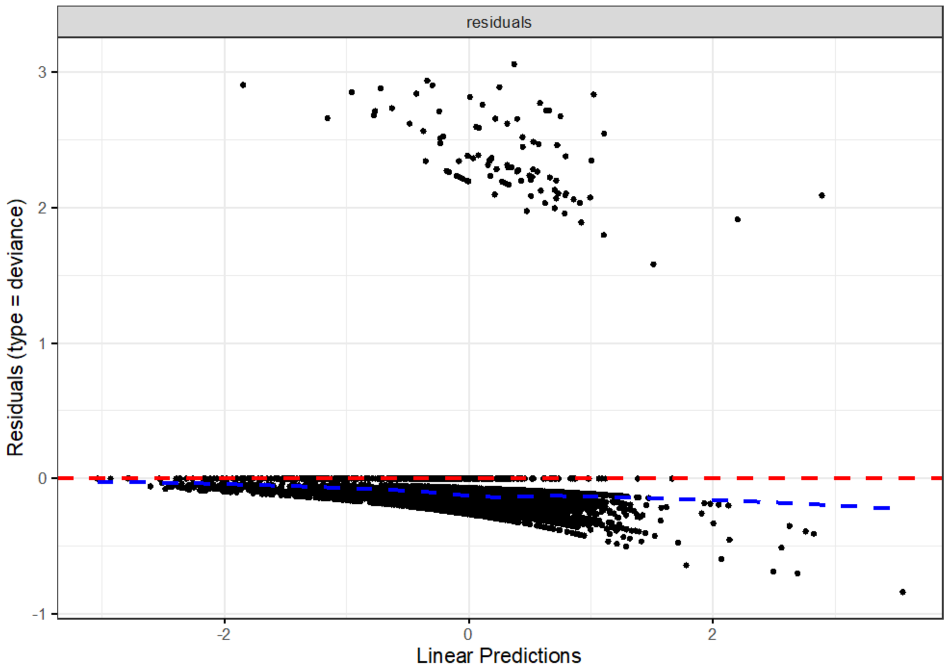
Index plots deviance residuals Model (3)



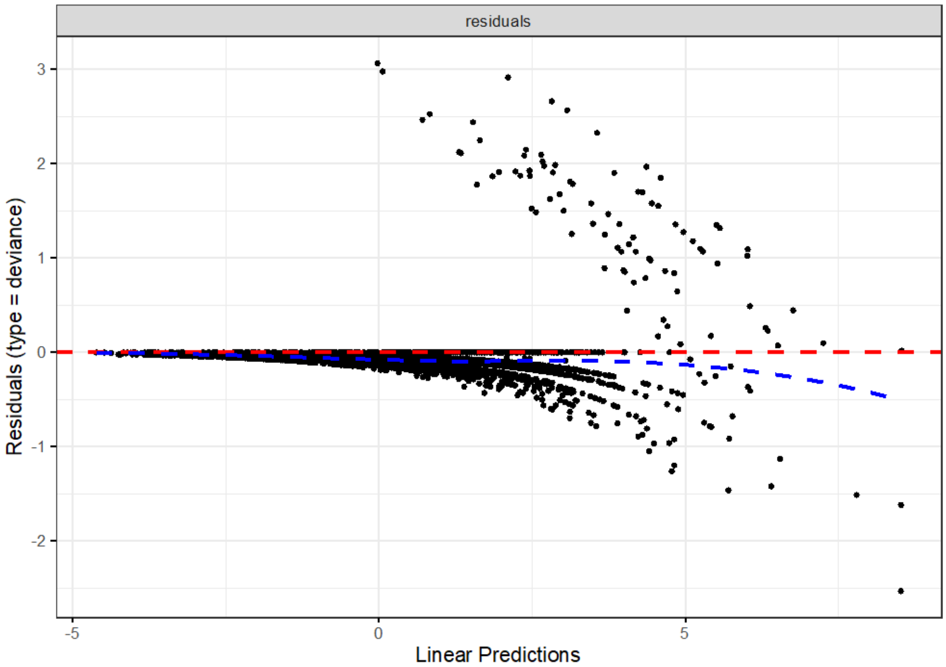
Index plots deviance residuals Model (4)



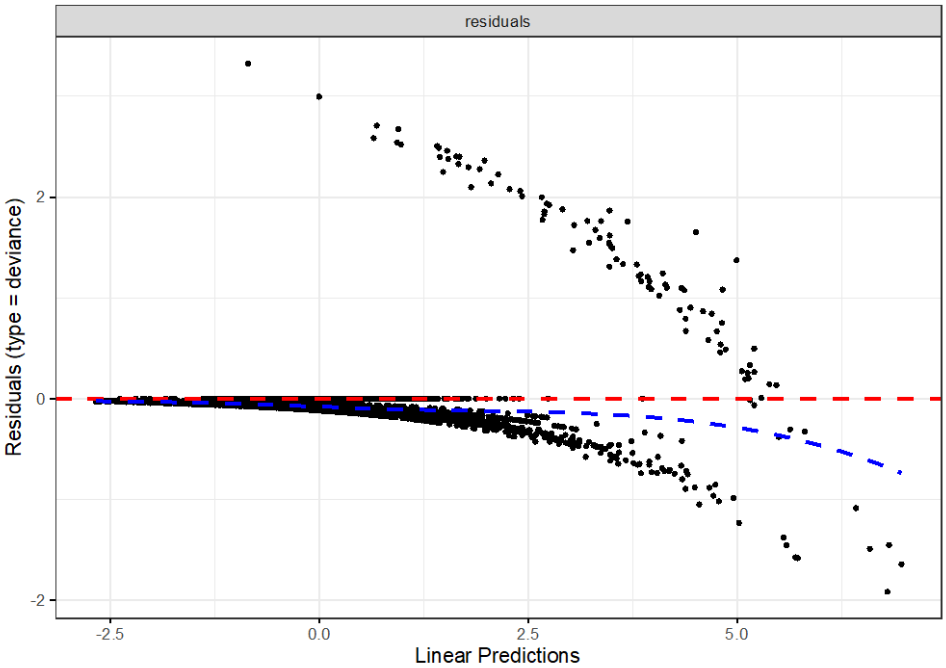
Index plots deviance residuals Model (1) *IND*



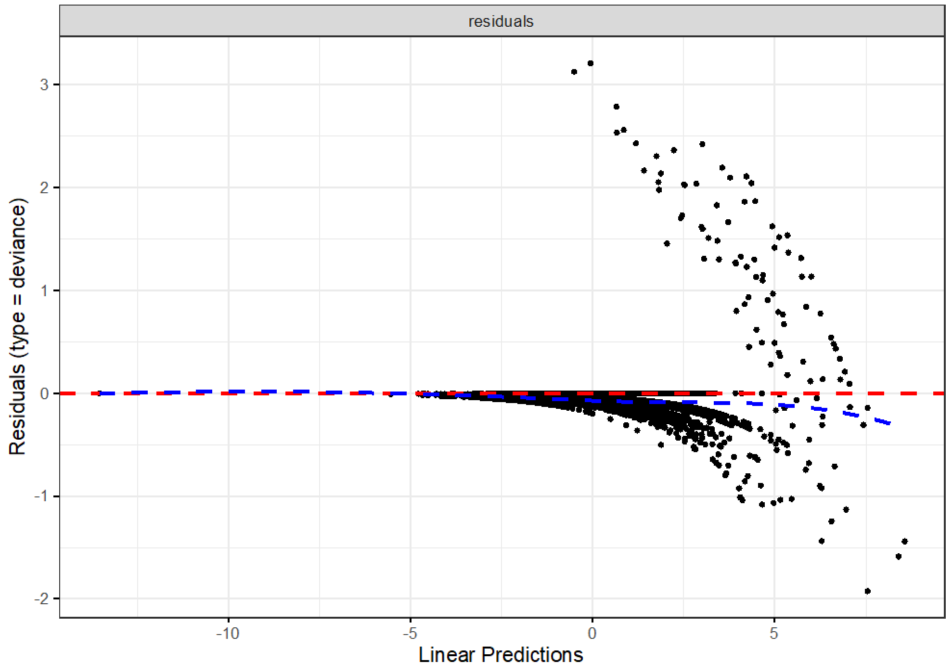
Index plots deviance residuals Model (2) *IND*



Index plots deviance residuals Model (3) *IND*



Index plots deviance residuals Model (4) IND

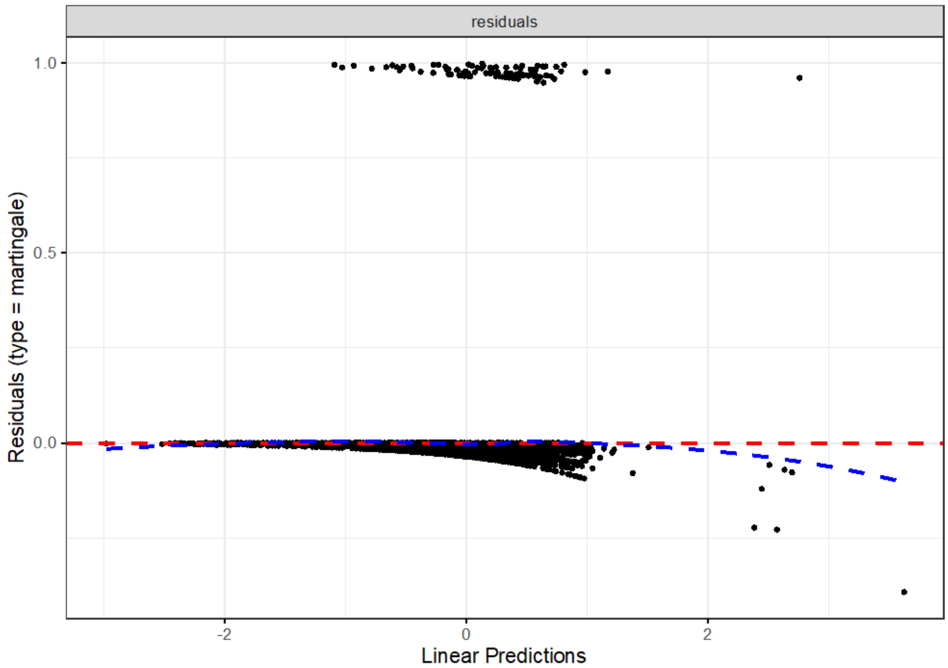


[Source: Author’s representation]

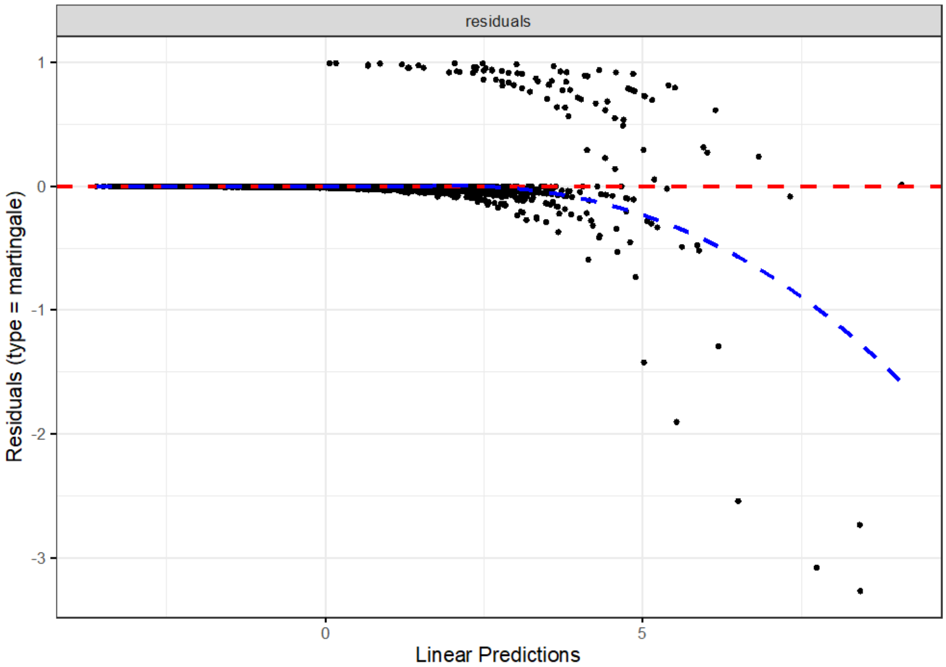
Appendix A-5.8: Graphical diagnostics of Martingale residuals

Index plots of Martingale residuals for Models (1) – (4) and Models (1) IND – (4) IND are presented to detect nonlinearity. Specifying the argument type=martingale in R illustrates the functional form of fitted models. The dashed blue line represents the local average for deviating residuals. The dashed red line indicates a horizontal line to highlight Y= 0 level.

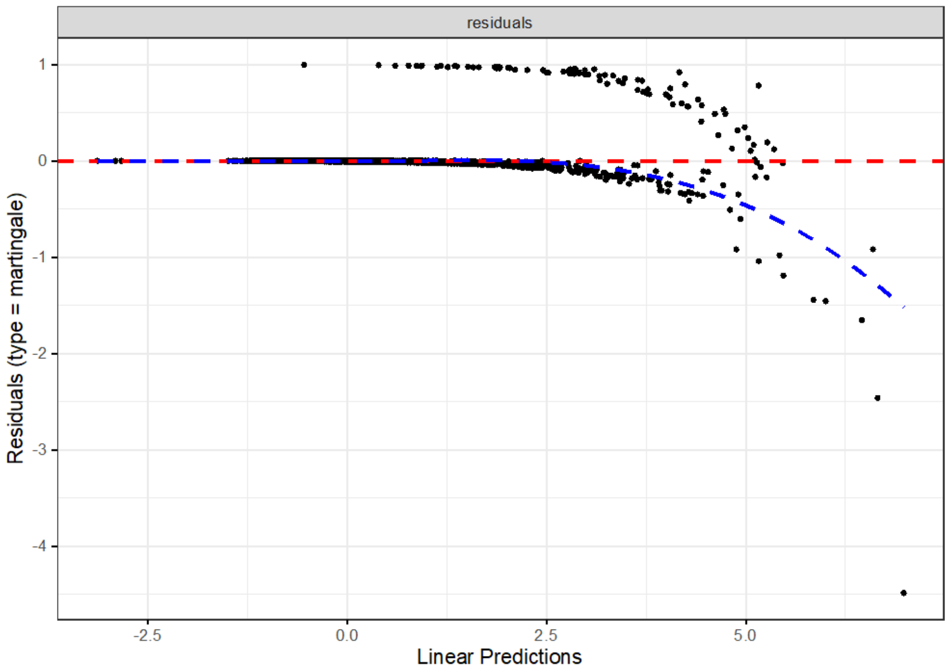
Index plots Martingale residuals Model (1)



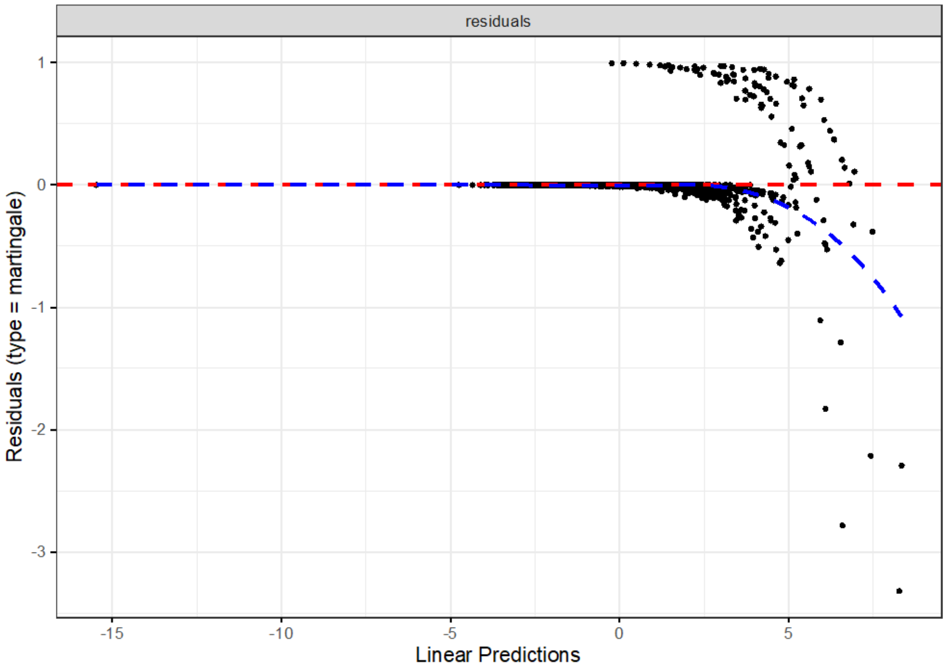
Index plots Martingale residuals Model (2)



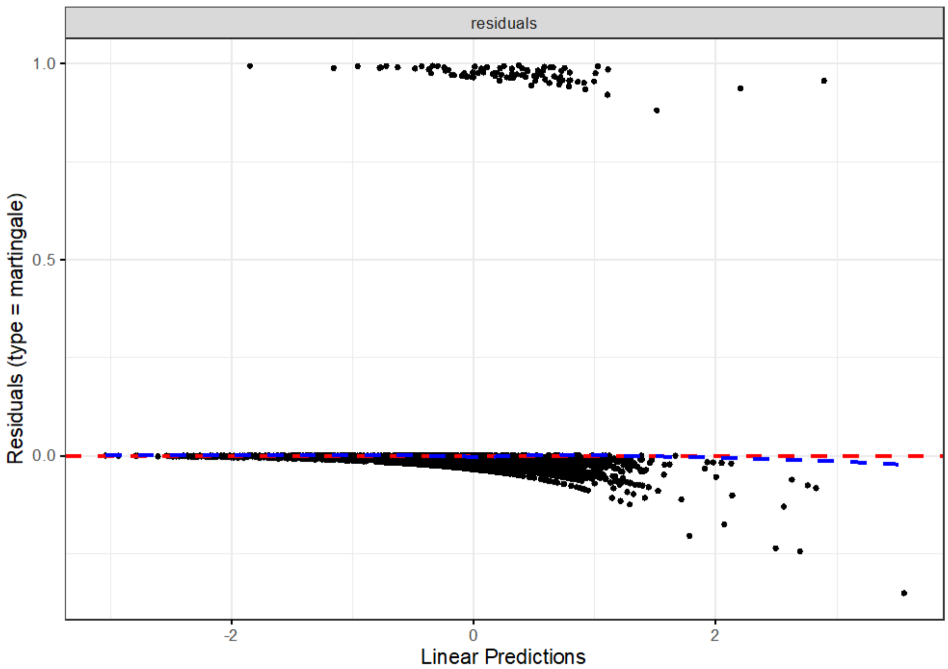
Index plots Martingale residuals Model (3)



Index plots Martingale residuals Model (4)



Index plots Martingale residuals Model (1) *IND*



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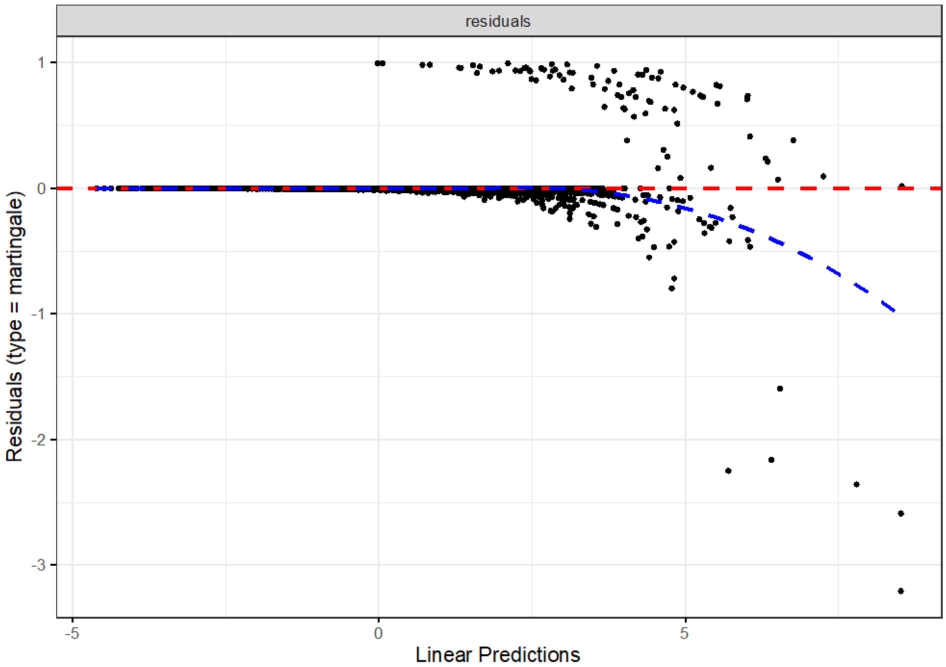
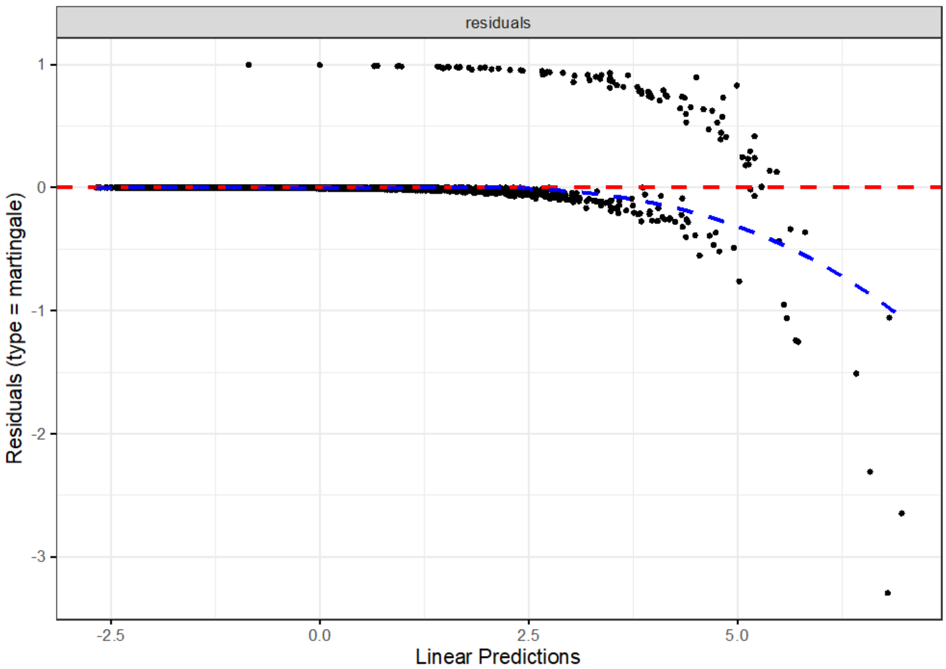
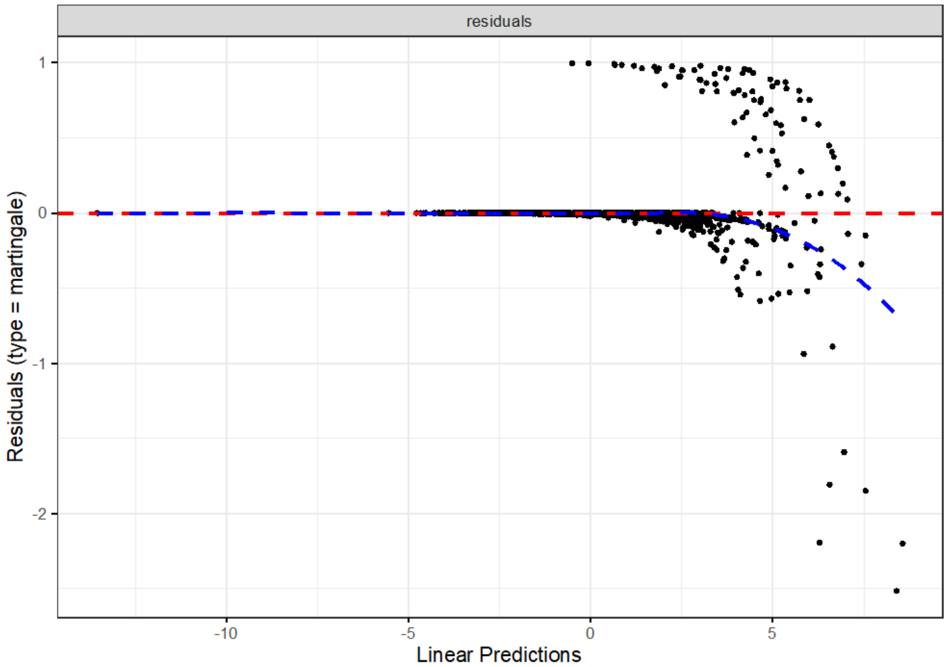


Index plots Martingale residuals Model (3) IND



Index plots Martingale residuals Model (4) *IND*



[Source: Author's representation]

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