PREDICTING CORPORATE FAILURE AND TURNAROUND

A Profitable Investment Approach

Rico Voigt Hansen – Student ID 101150

Sebastian Skylv – Student ID 93100

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Advisor: Christian Rix-Nielsen

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Abstract

This paper aims to answer the following question: Can predicted corporate failure probabilities be utilized in an investment strategy to generate an abnormal return, and can this return be further improved by adjusting the strategy according to predicted turnaround probabilities?

The paper builds on the research by Campbell, Hilscher and Szilyi (2008) and starts out by predicting probabilities of corporate failure using Shumway's (2001) dynamic logit specification. Distressed firms are defined in the paper as those belonging to the highest decile when firms are ranked according to their predicted probabilities of failure. Seven investment portfolios are then generated, experimenting with longing and shorting the distressed firms. Moreover, probabilities of corporate turnaround are predicted using a dynamic logit model. The analysis makes the unique contribution to the literature, that time spent in distress is a key determinant of the occurrence of corporate turnarounds. Finally, the predicted probabilities of turnaround are used as an attempt to enhance the returns of the optimal investment portfolio, by investing strategically in distressed firms with high probabilities of turnaround, while shorting those with low probabilities of turnaround.

Though the turnaround prediction model is found to accurately predict the occurrence of turnarounds, the relating adjustments are found to have no significant impact on the portfolio returns. Interestingly, the two portfolios proposed by Campbell et al. perform most poorly. The optimal investment portfolio is found to be that which only goes long in distressed firms. The excess return is computed as the portfolio alpha in a Fama and French five-factor model. This portfolio generates an average excess return on the American market of 5.5% over the period 1973-2004.

The authors suggest two main explanations of these findings: First, companies that are relatively distressed compared to the rest of the market are in general undervalued, and an abnormal return can be gained from investing in them. In contrast, Campbell et al. found that distressed companies were overvalued. Second, the underlying assumptions of the evaluation of excess return can be contested. Campbell et al. did not enter into a discussion of these assumptions. Aside from methodological biases arising from defining the concepts of failure, distress and turnaround and from modelling probabilities of failure and turnaround through a set of subjectively deemed relevant covariates, the authors of this paper highlight the importance of the assumption of a friction-free market. After accounting for such market frictions, the authors conclude that the premium on distressed stocks will diminish if not vanish altogether. These findings also challenge the abnormal returns reported by Campbell et al.

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Glossary

Abnormal return: Return that is not explained by the underlying risk of a stock or portfolio or its exposure to the factors of Fama and French's five-factor model and can instead be contributed to the stock-picking prowess of the investor. The alpha of the five-factor model will determine the **investment alpha**. If a positive investment alpha exists, there is an abnormal return. The value of the alpha is the magnitude of the abnormal return.

Bankruptcy filing: The extant literature often mentions Bankruptcy filings under Chapter 7 or 11 of the U.S. Bankruptcy Code as a measure for corporate failure. Bankruptcy filing under Chapter 7 refers to **liquidation bankruptcy** and results in the immediate liquidation of the company, whereas filing under Chapter 11 refers to **reorganization bankruptcy** that allows managers to reorganize their debt in an attempt to avoid liquidation. This paper uses a different measure of failure (see below definition of corporate failure).

Capital asset pricing model: (abbreviated 'CAPM') A model developed by William F. Sharpe (1964) which relates expected excess return of an asset and its systematic risk through a linear relationship. This model is used as a simple way to evaluate investment portfolio abnormal returns.

Corporate failure: (abbreviated 'failure') Relates to a company that has been delisted by the Center for Research in Security Prices (CRSP, 2019) with one of the following delisting codes: 552, 560, or 574.

Corporate turnaround: (abbreviated 'turnaround') Relates to a company that was distressed in period t-1 and is not distressed in period t.

Dynamic logit model: Refers to Shumway's (2001) logit specification, which incorporates each firm-month as a separate observation. This is equivalent to a **hazard model** (as explained in *Quantitative Method*).

Excess return: The return of a stock or portfolio over a specified benchmark. If no benchmark is specified, it is implicit that the benchmark is the risk-free rate.

Fama and French's (2015) five-factor model: (abbreviated 'five-factor model') An extension to the CAPM proposed by Eugene Fama and Kenneth French which includes four additional factors: size factor (SMB), value factor (HML), profitability factor (RMW) and the investment factor (CMA). This model is used as a more robust way to evaluate investment portfolio abnormal returns.

Financial distress: (abbreviated 'distress') Relates to a company that belongs to the highest decile when companies are ranked according to predicted probabilities of failure. Note therefore that the definitions of failure and distress are not interchangeable.

Firm: A business unit or enterprise. This term is used synonymously with the terms 'company' and 'concern'.

Market efficiency: Fama (1970) defines three types of market efficiency: weak, semi-strong and strong. These relate to the information reflected by stock prices. By 'efficient' we mean 'strong' market efficiency in Fama's wording.

Optimal dynamic logit model: Refers to the dynamic logit failure/turnaround prediction model which, after experimenting with several sets of covariates, yielded the highest pseudo R-squared.

Optimal investment portfolio: This paper presents seven different investment portfolios. The one that generates the highest investment alpha will be referred to as the optimal portfolio. This is also the portfolio with the highest Sharpe ratio.

Predicted probability of failure: (abbreviated 'probability of failure') Refers to the output probabilities of our optimal dynamic logit failure prediction model.

Predicted probability of turnaround: (abbreviated 'probability of turnaround') Refers to the output probabilities of our optimal dynamic logit turnaround prediction model.

Profitable investment strategy: A strategy that, on average, generates abnormal returns throughout the sample period.

Note that we will refer to our own chapters and sub-chapters throughout the paper by writing the relevant heading in italic.

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1. Introduction

1.1 Motivation

In the 1960's, the first appearance of the capital asset pricing model (CAPM) marked an important innovation within portfolio theory. The CAPM was later extended by Eugene Fama and Kenneth French to include two additional factors (Fama & French, 1996). Each factor has the aim of reflecting the exposure to a specific underlying type of risk of the given investment. Throughout the 21st century, scholars have identified close to 400 factors with strong statistical significance (Harvey & Liu, 2019). However, the empirical evidence seems challenged when it comes to dealing with distress risk. Relatedly, Campbell, Hilscher and Szilyi (2008) find, in their paper *In Search of Distress Risk,* that stocks that are relatively distressed compared to the general market are overvalued. They find that an abnormal return can be generated by shorting the companies that are most likely to fail in a year, while going long in companies that are least likely to fail. This return cannot be fully explained by neither Fama and French's three-factor model nor the Carhart four-factor model (Campbell, Hilscher, & Szilagyi, 2008). Campbell et al. argue thus that the market is ineffective, when it comes to valuing risky stocks.

Other studies have found contradicting evidence. Fama and French (1996; 2015) themselves find both their three-factor model and later their five-factor model to be able to explain stock and portfolio returns to a high degree. For all the test portfolios they set up, the models have an explanatory power R^2 of around ninety percent.

These findings lay the foundation of this paper. The main objective is to test the suitability of utilizing predictions of corporate failure and turnaround as stock-picking guidelines when generating an investment strategy. In other words, we will investigate if a profitable investment strategy can be generated from modelled probabilities of failure and turnaround.

1.2 Research question

CAN PREDICTED CORPORATE FAILURE PROBABILITIES BE UTILIZED IN AN INVESTMENT STRATEGY TO GENERATE AN ABNORMAL RETURN, AND CAN THIS RETURN BE FURTHER IMPROVED BY ADJUSTING THE STRATEGY ACCORDING TO PREDICTED TURNAROUND PROBABILITIES?

In this context, we aim to test firstly whether Campbell et al.'s (2008) approach to predicting corporate failure in their paper *In Search of Distress Risk* is replicable. Secondly, we aim to extend their analyses by applying the same statistical methodology to predict corporate turnarounds.

1.3 Review of Campbell et al.

The starting point of Campbell et al.'s (2008) analyses is the definition of corporate failure. They create a dummy variable which takes on the value 1 if the given firm is either bankrupted or failed as reported by the Kamakura Risk Information Services (KRIS). They then proceed to develop a statistical model which predicts aforementioned failures given a set of relevant covariates. Both the statistical model and the set of covariates are inspired by Shumway (2001). The model is a dynamic panel model that can be expressed using a classic logit-specification (see *3.6 Quantitative Method* for a thorough explanation of the mathematics behind the model). Campbell et al. (2008) experimented with different forecasting horizons ranging from 'now' to three years into the future. Deeming one year a realistic forecasting period, they proceed with the relevant logit estimates.

Now possessing the tools to predict failure one year in advance, Campbell et al. (2008) then rank the sampled firms according to their predicted probabilities of failure. From this, they define the most distressed firms as those belonging to the highest decile, i.e. the firms which are deemed more susceptible to experience failure in a year. Symmetrically, least distressed firms are defined as those belonging to the lowest decile. Subsequently, Campbell et al. (2008) generate simulated investment portfolios based on these different predicted relative levels of distress. The idea is to go long on the least distressed firms while shorting the most distressed firms.

Having created an investment portfolio, the authors now need a benchmark to evaluate the portfolio returns. The first and most basic benchmark is set out by the CAPM (see *2.7 Capital Assets Pricing Model* for an explanation of the model). The second, more comprehensive benchmark builds on the work of Fama and French (1996). Campbell et al. (2008) then estimate portfolio excess returns (over the market) by controlling for the three key risk factors identified by Fama and French (1996) along with a fourth factor identified by Carhart (1997). That is, they regress portfolio returns on the four risk factors and subsequently report the regression alpha. The reported alphas are, on average, positive throughout the sample period. Campbell et al. argue thus that the market is ineffective when it comes to valuing distressed stocks.

1.4 Hypotheses

H1: Campbell et al.'s approach to predicting corporate failures is replicable.

We assume that the findings of Campbell et. al. (2008) are replicable. Their work lay the foundations of our turnaround-model, as the distress and turnaround definitions we will work with in this paper are based on the failure probabilities found using the replicated model.

H2: Shorting companies with high probabilities of failure yields abnormal returns.

This hypothesis is based on the findings of Campbell et al. (2008). They show that by shorting companies with high probabilities of failure, one can consistently generate positive portfolio alphas. We replicate and test this investment approach, in order to construct the baseline for our third hypothesis.

H3: By developing and applying a theoretically sound and empirically accurate model for corporate turnarounds, the performance of the investment strategy that is based on failure probabilities can be further enhanced.

We hypothesize that an investment strategy, which focuses its stock-picking on distressed stocks can be improved if the selection of stocks for the portfolio is assisted by a measure of the firm's probability of experiencing a turnaround. Hence, a model that forecasts probabilities of turnaround will be developed in this paper and applied to an investment strategy that focuses on distressed companies.

1.5 Problem definition and approach

In the following, the scope of the paper is further clarified and justified.

Our starting point is to attempt to replicate the analyses performed by Campbell et al. (2008) with the objective of critically exploring the underlying assumptions, the drivers of their results, and the replicability of their results. To do so, we first replicate their dynamic logit model for corporate failure using identical variables and data sources. We then apply the results of this model to various investment strategies to see whether the predicted failure probabilities can be used to generate an abnormal return in the stock market.

Next, we construct a turnaround model using the same statistical approach as that of the failure model. This model is applied to the aforementioned investment strategies as an extension in an attempt to enhance the risk-adjusted returns by investing strategically in distressed firms with high probabilities of experiencing a turnaround.

To be able to assess if it is possible to generate a profitable trading strategy based on predicted probabilities of failure, we will first investigate which statistical tools and explanatory variables will allow us to predict such probabilities accurately. Similarly, to assess if it is possible to enhance our trading strategy based on predicted probabilities of turnaround, we must determine which statistical tools and explanatory variables will allow us to predict probabilities of turnaround accurately.

Once we have identified our optimal prediction models, we will need to determine their robustness to methodological biases and explore if the underlying assumptions necessary to implement the trading strategies are realistic.

We will use forecasted probabilities of corporate failure to define both financially distressed companies and companies that experience a turnaround. The literature does not provide a single supreme definition of *corporate failure*, *financial distress*, or *corporate turnaround*. Corporate turnaround is usually dependent on the definition of financial distress. Additionally, confusion might arise from the fact that some researchers use the following terms synonymously: default, bankruptcy, insolvency, organizational decline, corporate failure and financial distress, even though these terms describe different events. The definitions employed in this paper are included in the *Glossary*.

It is important to note that our selected definitions of turnaround and distress are *relative to the other companies* in our dataset. This entails that company A which was previously distressed could be classified as having achieved a turnaround simply because companies B and C have become more prone to failure, despite company A displaying exactly the same failure risk as before.

In *3. Methodology*, we discuss in detail the various implications of the selected definitions of 'distress' and 'turnaround'.

We restrict our analyses to determining predictors of corporate failure and corporate turnarounds. We do not attempt to examine the fate of firms once they have failed, nor do we attempt to examine the utility of strategic initiatives in regard to post-failure performance[1]. This is due to our interest in being able rather to *predict* corporate failure so that we can generate a profitable trading strategy.

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[1] See for instance Dawley & Hoffman & Lamont (2001) for lacks in literature regarding post-distress initiatives

When modelling both failure and turnaround probabilities, we select relevant covariates based on our literature review. However, due to lack of data, several relevant covariates will not be included in our final models, as it would significantly reduce our regression observations. For instance, our literature review suggests that changes in the number of employees can significantly explain a portion of the probability of turnaround. Yet including this variable in our logit-regression from *4. Analysis & Results* would substantially diminish our total observations, hence its exclusion.

Data have been collected on a monthly basis when possible. Since most financial data are available on a quarterly basis at best, we interpolate monthly values. This is also further explained in *3. Methodology*, where the potential implications of such interpolation are discussed alongside.

Given that we intend to replicate the analyses of Campbell et al. (2008) (see *3.3 Our Replication and Campbell et al. – Main Differences* for a detailed review of our replication), we match their sample period, which runs from year 1963 to year 2004. For the purpose of running out-of-sample tests of our final logit models and optimal investment portfolio, we also collect data for the period 2007-2018. The intents are twofold: testing our optimal investment strategies in an unrelated sample, as well as testing the robustness of our portfolios in a period of macroeconomic crisis.

Finally, the existing literature on corporate distress and turnaround is highly biased towards the U.S. and the U.K. Ideally we would want to run our analyses on data from other countries (at least as a robustness check). Nonetheless, due to data availability, we have decided to proceed with U.S. data only in order to achieve the highest number of observations and thus large-scale statistical models.

1.6 Contribution

To our knowledge, we are the first to replicate Campbell et al. (2008)'s investment strategy with the aim of critically reviewing the implications of their methodological choices, testing the replicability of their results, as well as extending the stock-selection process for the superior investment strategy by forecasting the occurrence of corporate turnarounds. Relatedly, we conduct a number of additional robustness checks in complement to the forth-bringing of economic arguments in order to ascertain what truly drives the abnormal portfolio returns found by Campbell et al. (2008).

Moreover, by replicating the analyses of Campbell et al. (2008), we contribute to the literature by making an almost perfect comparison between our results possible. We say 'almost perfect' because small differences in data collection and methodology highlighted later on could cause a direct comparison to be slightly biased.

Furthermore, we add to the extant literature on turnaround modelling by applying a definition of distress that is relative to the market as a whole. Moreover, we investigate the importance of a variable describing time spent in distress, which, to our knowledge, has received very little attention in the literature. On top of time spent in distress, we investigate a multitude of other potential covariates in order to secure the highest explanatory power possible. Under the assumption that the companies in our dataset on average perform smart investments when they increase their assets, we support that the effect of these investments is significant when they are performed early in the distress-period.

Finally, we combine turnaround modelling and portfolio theory in order to investigate whether it is possible to generate a profitable trading strategy based on our optimal turnaround model.

1.7 Outline

The paper proceeds as follows. *2. Literature review* gives a critical review of relevant literature and develops the conceptual framework of the research. *3. Methodology* outlines the research design and justifies our methodological choices. *4. Analysis & Results* provides a presentation and interpretation of our results in relation to the research questions. *5. Discussion of the Robustness of the Results* and *6. Limitations* critically assess the limitations of the analyses. *7. Conclusion* presents the conclusions of the paper. Finally, *8. Further Research* provides pointers for further research. The tables supporting our analyses are presented in *Appendices* (Appendices A-W) along with an overview of variables (Appendix X), figures (Appendix Y) and the raw Stata code (Appendix Z).

2. Literature Review

In the following, we critically review the relevant literature and develop the conceptual framework needed for our analyses. The Chartered Association of Business Schools has formulated an academic journal guide to the relative quality of journals in which business and management academics publish their research. The latest guide has been developed for the year 2018 and incorporates a total of 1582 journals. Journals are ranked on a scale from one to four-star, where 4* marks the highest score, reflecting journals of distinction. The literature presented in this chapter mostly stems from journals ranked 3 or higher, which speaks for the exceptional quality of our sources. 4*-rated journals display a quality that is world-leading in terms of originality, significance and rigor. 3-rated journals display a quality that is internationally excellent in terms of originality, significance and rigor (Chartered Association of Business Schools, 2019).

2.1 Corporate failure and distress

Before we can attempt to model corporate failure and distress, we need to assert the relevance of these subjects as well as define the core concepts. The extant literature provides a myriad of definitions of severe declines in performance, which we will present to the reader.

2.1.1 Origins and relevance of corporate failure and turnaround research

Corporate failure and turnaround have been two topics that – going hand-in-hand – have occupied scholars for several decades. The foundations of the research go back to the 1970's and 1980's (Altman 1968; Bibeault 1982; Gordon 1971; Hambrick & Schecter 1983; Hofer 1980; Schendel & Patton 1976; Schendel, Patton & Riggs. 1976). The relevance of these topics stems primarily from the many actors that would benefit from an understanding of the events of failure and turnaround. Regulators might wish to more accurately predict failure in order to develop the necessary precautionary policies to avoid a country-wide recession. Firm managers certainly wish to accurately predict failure in order to take the necessary measures to remain a going concern. Banks and other providers of credit to companies want to measure the risk of these companies in order to determine appropriate loan rates. Finally, investors might benefit from a deep understanding of distress and turnaround in that they could potentially generate profitable trading strategies based on their forecasts.

Aside from the many interested actors, a major policy change in the Unites States in the late 1970s led to a significant increase in bankruptcy filings, thus accentuating the interest in research on corporate failure. In 1978, the Bankruptcy Reform Act ("the Act") was adopted with the aim of pushing company managers to reorganize the firm rather than to liquidate it when faced with times of financial distress (Bradley & Rosenzweig, 1992). The inherent thinking was that from a macroeconomic perspective *"… it is more economically efficient to reorganize than liquidate, because it preserves jobs and assets."* (U.S. Code Congressional and Administrative News, 1978, supra note 2). Although it will not be the aim of this paper to discuss the advantages and shortcomings of this reform, we mention it, because after the Act was enforced on October 1st, 1979, the number of bankruptcy filings increased substantially, which led to a wave of research on the topic (Johnson, 1996; Markides, 1995). Likewise, the economic crisis of 2008 significantly increased the amount of bankruptcy filings, thereby entailing a second wave of research. Since there is an average publication lag of around seven years, this second wave of research is predicted by Schweizer and Nienhaus (2017) to run from 2015 and onwards which accentuates the current relevance of the subject. The extant literature on corporate turnarounds has been summarized thoroughly by Schweizer and Nienhaus (2017) who have studied almost 300 research papers published in 25 different journals within the fields of economics, accounting, finance, management, and sociology. Preceding summarizations of the extant literature include the review of Trahms, Ndofor and Sirmon (2013) and that of Robbins and Pearce (1992).

Empirical evidence suggests that most firms will experience a sustained decline in performance at some point in time. Relating to the first wave of bankruptcy filings described previously, Schendel and Patton (1976) find that a third of the firms contained in the Standard and Poor's 500 index experienced at least one four-year period of uninterrupted decline in profitability between 1951 and 1970. Relating to the second wave of bankruptcy filings described previously, Trahms et al. (2013) report that half of the firms contained in the Standard and Poor's 500 index experienced at least three years of declining profitability between 2005 and 2010. These findings greatly motivate the attempt of this paper at developing strong statistical models to predict failures (and thereby defining distress, cf. respective definitions in *Glossary*) and turnarounds.

2.1.2 Defining corporate failure and distress

As previously stated, many synonymous terms appear in the literature to describe a deterioration of company performance that threatens its existence. Among others are the notions of corporate failure, default, bankruptcy, insolvency, financial distress and organizational decline. The definition employed in this paper is set out in the *Glossary* (see definition of corporate failure). If other concepts are employed throughout this literature review, it will only be to accurately report the findings of other researchers.

2.1.3 Alternative definitions

The literature provides almost as many different definitions of decline in performance as there are papers. We present this myriad of definitions to the reader after which we discuss the implications of such conceptual disharmony. To create some cohesion, we have grouped definitions that were similar in the metrics they used to quantify decline in performance.

2.1.3.1 Bankruptcy filings

Several studies use bankruptcy as a measure of the ultimate decline in performance of a firm. Davidson, Worrell and Dutia (1993) use bankruptcy announcements in the Wall Street Journal to designate failed firms. Similarly Daily (1995) as well as Moulton and Thomas (1993) use bankruptcy filings under Chapter 11 of the U.S. Bankruptcy Code, whereas other scholars use bankruptcy filings under Chapter 7 of the U.S. Bankruptcy Code (Thornmill & Amit, 2003; Latham & Braun, 2009; Sheppard, 1994; Daily & Dalton, 1994; Daily & Dalton, 1995; Daily, 1996; Moulton, Thomas, & Pruett, 1996). The difference between a bankruptcy filing under Chapter 7 and 11 is that the former yields immediate liquidation of the company whereas the latter allows the firm to potentially re-emerge as a going concern if it can reorganize its debt (through renegotiations of existing debt contracts in terms of interest rates for instance) satisfactorily. Unsuccessful debt reorganizations under Chapter 11 will force the firm to file for straight liquidation bankruptcy through Chapter 7.

The advantage of using bankruptcy filings as a means to study corporate failure is that it is a 'certain' measure since it guarantees to only identify firms which have bankrupted. However, in doing so, it fails to recognize all the firms which may have been on the verge of bankruptcy yet somehow surviving. This has led researchers to investigate corporate distress rather than corporate failure.

2.1.3.2 Profitability measures

One approach to researching distressed companies without looking at bankruptcy is to focus on the profitability of the companies. Scholars have used several profitability measures to proxy for declines in performance which they consider particularly threatening to the existence of the firm. Put differently, scholars have used such metrics to arbitrarily define when a firm is distressed (i.e. on the verge of bankruptcy). Profitability measures that have been employed include return on equity (ROE), return on assets (ROA), return on sales (ROS), return on investment (ROI), return on invested capital (ROIC), earnings per share (EPS), and net income (NI) (Winn, 1997; Audia & Greve, 2006; Chen & Hambrick, 2012; Barker, Patterson, & Mueller 2001; Barker & Mone, 1994; Bruton, Ahlstrom, & Wan, 2003; Morrow, Johnson, & Busenitz, 2004; Bolton, 1993; Bruton, Oviatt, & White, 1994; Barker & Duhaime, 1997; Wiseman & Bromiley, 1991; Greve, 2011; Ndofor, Vanevenhoven & Barker, 2013). Some scholars use only one profitability measure. Others use a combination. Occasionally adjustments are made to the raw measure. For instance, Bruton, Oviatt, and White (1994) normalize net income by the gross national product growth rate. Another example is a paper written by Wiseman and Bromiley (1991) in which the authors adjust sales for inflation.

The immediate implication of using the aforementioned profitability metrics to define distress is that one then needs to define for how long a period the decline in the selected profitability measure needs to be sustained for us to talk about distress. Regardless of the measure adopted, Chen and Hambrick (2012) importantly argue that to capture distressed firms, the firms' performances had to be reasonably good before they declined, seeing that the aim is not to capture firms which are stagnating or slowly deteriorating. The mentioned scholars have used different decline durations ranging from two to five years. Moreover, some researchers impose that the declines in performance have to be uninterrupted, while others, more loosely, require a decline in x out of y years. By imposing uninterrupted declines, researchers encounter the obvious limitation that they will fail to capture firms that for instance have one 'good' month and 23 'bad' months within a two-year period, although such a firm might be expected to be almost just as bad as a firm which had 24 'bad' months. By requiring a decline in x out of y years instead, researchers overcome this limitation. Yet the 'x' and 'y' along with the distress proxy remain arbitrarily selected.

The second implication of using profitability measures, is that it entails the implicit assumption that changes in distress can be directly related to changes in the selected profitability measure. To illustrate why this assumption might not hold in some cases, let us say that we model corporate distress as a two-year uninterrupted decline in earnings per share (EPS). An otherwise healthy firm might then be categorized as distressed simply because it chose to spend all its excess gross profit on research and development (which thus diminishes net income, and EPS in turn).

2.1.3.3 Benchmarked performance

Some scholars require a continuous decline of any magnitude as long as it is a decline (Bruton, Ahlstrom, & Wan, 2003; Wiseman & Bromiley, 1991). Others require the decline to be of higher magnitude than a certain arbitrary threshold (Winn, 1997; Ndofor, Vanevenhoven, & Barker, 2013; Anand & Singh, 1997). Thirdly, some scholars define the decline as based on a performance-benchmark. This benchmark could be the past performance of the same firm (Audia & Greve, 2006; Chen & Hambrick, 2012; Gomez-Mejia, Haynes, Nunez-Nickel, Jacobson, & Moyano-Fuentes, 2007). Alternatively, the benchmark could be the performance of a peer group (Audia & Greve, 2006; Greve, 2011) or the performance of the industry (Filatotchev & Toms, 2003; Barker & Mone, 1994; Anand & Singh, 1997; Wan & You, 2009). Lastly, a set of other benchmarks have been used. For instance, Morrow, Sirmon, Hitt and Holcomb (2007) use market expectations and investor expectations as benchmarks. Another example is Barker and Duhaime (1997) who use the risk-free return as benchmark for the return on invested capital. Although the benchmark selection, to some extent, depends on the selected distress proxy, the discord between researchers highlighted above makes comparability of the studies impossible or at least non-credible.

2.1.3.4 Alternative measures

Other measures that have been used to identify distressed firms include credit spread differences (Benmelech & Bergman, 2011), the number of patents and R&D investments (Acharya & Subramanian, 2009), earnings before interest and taxes minus capital expenditures minus interests (Eichner, 2010; Pun & White, 2005), or even survey-based subjective measures (Carmeli & Schaubroeck, 2006; Schick & Ponemon, 1993).

2.1.4 Implications of a fragmented literature

In addition to the arbitrary nature of the definitions of corporate failure and distress pointed out in this chapter, the conceptual disharmony among researchers impedes comparability of different papers. This creates a separation between the results of each paper rather than letting one build on another. In this regard, we contribute to the extant literature by replicating the analyses of Campbell et al. (2008), thus making an almost perfect comparison between our results possible and plausible. We say 'almost perfect' because small differences in data collection and methodology highlighted later on could cause a direct comparison to be slightly biased.

Having reviewed the literature on failure and distress definitions, we now turn to review the framework necessary to adequately predict the occurrence of failure.

2.2 Failure prediction models

2.2.1 Traditional ratio analysis

The interest in predicting corporate failure accurately goes a long way back. Preceding the complex quantitative models we know today, scholars initially mapped specific characteristics of *continuing* vs *discontinuing* firms in the 1930's (Merwin, 1942). Several studies concluded that financial ratios could be used in order to predict bankruptcy effectively (Smith & Winakor, 1935; Hickman, 1958; Beaver, 1966; Tamari, 1966). However, all these studies were univariate in that they would consider only one ratio at a time. This spurious methodology led each study to different conclusions. For some businesses, a given profitability measure would prevail as the best predictor of failure, whereas in other cases, a different profitability measure or liquidity measure, or some other ratio would prove itself as the best predictor of failure.

2.2.2 Multiple discriminant analysis

Extending the idea of using a single ratio as a determinant of corporate failure, the first to receive broad recognition for his development of a multivariate model in order to predict corporate failure was Edward I. Altman (1968). Altman published a model based on an initial matched sample of 66 manufacturing firms for which financial data were obtainable. The core idea was to delimit all firms into two mutually exclusive groups: the (33) failed firms and the (33) non-failed ones. Failed firms were defined as having filed for bankruptcy under Chapter 10 of the National Bankruptcy Act (now incorporated in Chapter 11 of the Bankruptcy Code). The issues then became to (1) identify which ratios adequately characterize failed firms relative to non-failed firms, and (2) weigh the selected ratios accordingly, (3) by using an objective and appropriate statistical estimation method. After experimenting with different variables Altman (1968) identified five ratios which were doing the best overall job of predicting corporate failure.

Then, using discriminant analysis – a statistical method which we will not describe in this paper – Altman (1968) estimated the optimal weights for each of the selected ratios X_1-X_5. The best discriminant function was found to be as follows.

Altman's Z-score

$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5$

X_1 = Working capital / total assets | Working capital = current assets - current liabilities,
X_2 = Retained earnings / total assets,
X_3 = Earnings before interest and taxes / total assets,
X_4 = Market value of equity / book value of total assets,
X_5 = Sales / total assets

To generalize his results for practitioners without access to computing power, Altman (1968) defined optimal boundaries for the discriminant function. To select those boundaries for the Z-value, he investigated the predictive accuracy of his own model on his own sample. That is, he observed which firms would be misclassified (i.e. modelled as failed when in reality they did not fail, and vice versa) by his discriminant model if he were to run it on his initial sample. Altman (1968) thereby concluded that (1) firms which have a Z-score above 2.99 undoubtedly correspond to non-failed firms; whereas (2) firms which have a Z-score inferior to 1.81 undoubtedly correspond to failed firms. Finally, (3) firms which have a Z-score in between those two boundaries of 1.81 and 2.99 could not evidently be classified as either failed or non-failed, for these firms he conceptualized a "grey zone". Although prominent at the time, Altman's (1968) framework has later been subject to criticism. Most importantly, Shumway (2001) defies the statistical groundings (the discriminant method) and argues that such a static deterministic model is much less effective than a dynamic logit model (more details on this later in this chapter).

Despite this criticism, much research have been published, which support Altman's (1968) idea of the framework of a discriminant model when predicting corporate distress (Altman, 1983; Taffler, 1984; Theodossiou, 1991; Ohlson, 1980; Zmijewski, 1984; Agarwal & Taffler, 2008).

2.2.3 Merton's distance to default model

Others have expressed their concern regarding the absence of theoretical groundings of such traditional accounting-ratio-predicated models. This has led to the exploration of an alternative methodology for predicting corporate failure – the contingent claim valuation (i.e. option valuation). The starting point of a contingent claim valuation is to view equity as a call option on the firm's assets with a strike price equal to the value of debt. In this regard, Merton (1974) developed a revolutionary and theoretically sound structural model which relates the option value of assets to the risk of corporate failure.

Focusing on the results and intuitions of the framework rather than the explicit model derivation and assumptions, the contingent claim valuation solves the problem of unobservable market values of assets and liabilities by exploiting their link to the market value of equity[2]. Merton defines this relationship by using stochastic modelling and assuming lognormally distributed asset returns:

$$Equity = Assets * N(d_1) - Liabilities * N(d_2) * \exp(-rT)$$

, where *r* = risk-free interest rate, *N* is cumulative standard normal distribution *T* is time to maturity of liabilities, σ_{Assets} is the volatility of assets.

$$d_1 = \frac{\log\left(\frac{Assets}{Liabilities}\right) + (r + 0.5\sigma_{Assets}^2)T}{\sigma_{Assets}\sqrt{T}}$$

$$d_2 = d_1 - \sigma_{Assets}\sqrt{T}$$

Failure occurs if the value of assets fall below the value of debt. That is, if the above modelled value of equity falls below zero. To assess the risk of this happening, Merton further defines the concept of distance-to-default. Intuitively, this can be viewed as the number of standard deviations between the expected value of assets at maturity, and the default point:

$$Distance\ to\ default = \frac{\log(Assets) + \left(\mu_{Assets} - \frac{\sigma_{Assets}^2}{2}\right)T - \log(Liabilities)}{\sigma_{Assets}\sqrt{T}}$$

Here, μ_{Assets} = expected return on assets.

A more convenient way of expressing the default risk of the firm is to express it in terms of probability of default rather than the distance-to-default:

$$Probability\ of\ default = 1 - N(Distance\ to\ default)$$

Despite its strong theoretical groundings, Merton's distance-to-default model has later been the subject of criticism. Bharath and Shumway (2008) conclude that Merton's model – though having a useful functional form – does not yield as accurate probabilities of default as a dynamic logit model. Moreover, Hillegeist, Keating, Cram and Lundstedt (2004) point out two structural issues with implementing Merton's model. First, the assumptions of the model are restrictive in nature. For instance, one needs to assume that all liabilities have the same maturity and that the debt contracts have no safety covenants.

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[2] For book values, Equity = Assets – Liabilities. However, for market values, we need to build a stochastic model.

These assumptions rarely hold in practice, which might entail the predicted probabilities of default to be misspecified. Second, the model requires input parameters which are unobservable (for instance, asset volatility), thereby requiring the practitioner to estimate those parameters at the risk of measurement errors.

2.3 Dynamic logit models

To surmount the shortcomings of discriminant models and contingent claim valuations, Shumway (2001) develops a dynamic logit model to forecast probabilities of failure. This paper builds on Shumway's specification, which is therefore described thoroughly in *3.6 Quantitative Method*. Thus, in this literature review, we will simply highlight the revolutionary aspect of Shumway's framework. Indeed, Shumway's paper reveals that half of the variables thought statistically significant when predicting corporate failure using discriminant analyses become highly insignificant when using a dynamic logit specification. This suggests that much of the preceding research that has been done on corporate failure should be reassessed. The superior forecasting performance of Shumway's model relative to Altman (1968) and Zmijewski (1984) is confirmed by Chava and Jarrow (2004). Agarwal & Bauer (2014) support these findings and extend the conclusion to incorporate the relative performance of contingent claims valuations as well. This said, Mousavi and Ouenniche (2018) criticize previous evaluations of relative performance of different predictions models due to the comparability assessment methodology employed. To compare the relative performance, one needs to define a measure of performance. Preceding evaluations have defined several measures of performance and thereafter evaluated the relative performance using the measures one by one, which has led to conflicting results. Mousavi and Ouenniche (2018) overcome this limitation by developing a complex framework and conclude among other things that dynamic models are superior to static ones. Since we have not yet introduced the reader to the concepts of dynamic vs static modelling (see *3.6 Quantitative Method*), we note here that Shumway's (2001) model is dynamic, whereas Altman's (1968) and Merton's (1974) are static.

2.4 Accounting-based vs market-based models

As a last point of discussion regarding failure prediction models, we turn to address the relative merits of accounting-based models versus market-based models. Put differently, models which use accounting values of the explanatory variables relative to models which use market values of the explanatory variables. Discriminant models mentioned previously serve as a good example of accounting-based models, whereas Merton's (1974) model can serve as a good example of a market-based model.

2.4.1 Flaws of accounting data

Agarwal and Taffler (2008) highlight potential flaws related to the use of accounting data in failure prediction models. Firstly, financial accounting statements solely depict past performances of firms at specific points in time, which does not necessarily guarantee any information about the future performance. Secondly, asset values are often measured using historical cost accounting, which values the assets at their original cost when acquired by the firm. Thus, true asset values might greatly differ from the recorded book values. Thirdly, financial accounting statements can be manipulated by firm executives as many accounting standards include subjectivism to a certain extent. Fourthly, accounting statements are prepared on the basis of the going-concern principle, which inherently assumes that that firm will not fail.

2.4.2 Merits of market data

Many of these flaws can be mitigated by using market data instead. First, stock prices are forward-looking in that they reflect the present value of the expected future cashflows, hence they are more fitting for forecasting purposes. Second, if one believes that the market is efficient[3], stock prices should include all relevant publicly available information (i.e. accounting statements) along with all privately available information. The general consensus is to view the market as semi-strongly efficient (Brealey et al., 2019). The efficiency of the market thereby increases the validity of using market data contra accounting data when predicting corporate failure. Third, market values are available at all times, not simply at specific points in time. Fourth, market data are not subject to manipulation through accounting methodologies.

2.4.3 Empirical evidence

Despite the mentioned merits of using market data rather than accounting data, Agarwal and Taffler (2008), surprisingly, conclude no significant difference in the predictive ability of failure prediction models. This said, their investigation compares two types of static models whose flaws have been mentioned already and will be further elaborated in *3.6 Quantitative Method*. More expectedly, Chava and Jarrow

[3] Fama (1970) defines three types of market efficiency: weak, semi-strong and strong. These relate to the information reflected by stock prices. By 'efficient' we mean 'strong' market efficiency in Fama's wording.

(2004) conclude that the addition of accounting variables to a failure prediction model which contains market variables yields no additional predictive power. In other words, market variables are at least as good, if not better, predictors of corporate failure. Shumway (2001) and Campbell et al. (2008) further support the use of market variables as an alternative to accounting variables.

2.5 Corporate turnaround

Having addressed the concepts of failure and distress along with the statistical modelling of failure, we now turn to review the literature on turnarounds. Before we can attempt to later model turnaround, we will need to define it. The literature provides a myriad of definitions, which are however closely related to the aforementioned definitions of distress. The symmetrical nature between the concepts of distress and turnaround will be addressed along with potential shortcomings of the turnaround definitions. Subsequently, we proceed to discuss specific strategic actions recommended by the scholars in support of achieving a turnaround. Moreover, the intensity and timing of such strategic actions will be addressed.

2.5.1 Defining turnaround

2.5.1.1 Symmetrical opposition of distress

Hofer (1980) posits that most companies which experience severe declines in performance will make attempts to remediate this decline. If the decline in performance is significant enough for the company to reach a state of distress, a remediation becomes even more crucial (Asquith, Gertner, & Scharfstein, 1994). Most turnaround metrics can somewhat be related to the basic definition proposed by Schendel et al. (1976, p. 3) as *"a decline and recovery in performance".* For instance, Chowdhury (2009) provides a quite intuitive definition of turnaround as surviving a performance deterioration that put the firm's existence at risk. These two similar definitions both highlight the interdependency or even symmetry between the arbitrary concepts of distress and turnaround. That is, a turnaround cannot occur unless there is something to turn around from. To illustrate the symmetry between distress and turnaround, we use the paper written by Barker and Mone (1994) as an example. They defined distress as a simultaneous decline in return on investment and return on sales for a minimum of two consecutive years. A turnaround was then defined as a simultaneous increase in return on investment and return on sales for two consecutive years. Due to this symmetry in definitions, the same metrics and arbitrary biases apply to both definitions, hence we will not repeat the arguments set out when defining distress. This said, it is worth noting that researchers who study bankruptcy rather than distress do not necessarily symmetrically match the definition of turnaround as simple survival, but rather define partial turnaround as the firm maintaining at least fifty percent of its assets after reorganizing debt under Chapter 11 of the U.S. Bankruptcy Code (see for instance, Moulton and Thomas (1993) and Daily (1995)).

2.5.1.2 Transition period between distress and turnaround

Recent studies have commonly allowed for a transition period between decline and recovery (Chowdhury, 2009; Tangpong, Abebe, & Li, 2015). The transition period is meant to accommodate a certain stabilization and/or slow recovery of the firm without imposing an immediate turnaround from one month to another. Nevertheless, there is a natural boundary to how long a firm can remain distressed before inevitably becoming insolvent (Winn, 1993). Moreover, the selection of the duration of the transition period yields yet another arbitrary choice. Hence, besides imposing a selection bias, the definitional discord between researchers creates, as mentioned previously, problems of comparability of different studies.

2.5.2 Defining turnaround stages

Aside from disagreeing on the exact definition of turnaround and transition period, researchers likewise seem to disagree when it comes to defining what the different stages of a turnaround are, in what order they appear, and how long they last (Schweizer & Nienhaus, 2017). This said, most definitions can be combed together into a preliminary stage of retrenchment, followed by a stage of recovery (Eichner, 2010), though this dichotomous categorization has been the subject of criticism (Barker & Mone, 1994; D'Aveni, 1989). Thus, turnaround actions that happen for firms under distress can be classified as either *defensive* (relating to the phase of retrenchment) or *stabilizing* (relating to the recovery phase) (Arogyaswamy, Barker & Yasai-Ardekani, 1995; DeWitt 1993; Domadenik, Prašnikar & Sveinar, 2008; Hambrick & Schecter, 1983; Pearce & Robbins, 1993). This dichotomous classifications of turnaround strategies inspired our later selection of covariates when forecasting turnaround probabilities. Indeed, in *4. Analysis & Results*, we explore the significance of several covariates that reflect firm changes during the first six months, twelve months, eighteen months, and twenty-four months in distress. Retrenchment may then be equivalent to the first year in distress, while recovery may be the second year in distress. However, we will not need to specifically define the periods of retrenchment and recovery because the purpose of this paper is not to gather support regarding such arbitrary definitions, but rather to understand the effectiveness of different turnaround actions at different points in time. Indeed, some covariates are found to be statistically significant only in the early stage. More details will follow in *4. Analysis & Results*.

Figure 1: Turnaround stages

Note: This figure depicts the different stages of a firm along with the optimal strategy actions from the moment it enters distress to the moment it manages to successfully turn around.

Source: Own computation, based on literature review.

Three immediate questions spring from above descriptions of turnaround and depiction of the process. What kind of strategic measures can be implemented to secure a successful corporate turnaround? How intense should these measures be? When should one aim to implement them? These questions will be addressed in turn.

2.5.3 Retrenchment phase

2.5.3.1 Which defensive actions?

If a firm enters distress, a period of retrenchment appears unavoidable (Robbins & Pearce, 1993). Defensive actions are conducted during the retrenchment phase and have the sole purpose of stopping the distress from becoming bankruptcy (Bibeault, 1982), i.e. achieving short-term stability. Defensive actions are usually manifested as cost and asset reductions (Trahms, Ndofor & Sirmon, 2013). Barker and Duhaime (1997), and Chowdhury and Lang (1996) find that defensive actions enable firms to have a higher likelihood of experiencing a turnaround. In other words, the retrenchment phase is a necessity for a successful turnaround. However, the literature presents fragmented evidence regarding the effectiveness of defensive actions. Firstly, to achieve short-term stability, firms are encouraged to focus primarily on actions which improve the immediate liquidity position of the firm (Finkin, 1985). However, Castrogiovanni and Bruton (2000) find that the retrenchment-oriented actions vary in effectiveness according to the context of the firm. Specifically, the industry conditions are found to be of importance when determining the success of retrenchment actions (Morrow, Johnson & Busenitz, 2004). Another example of context which is found to be determining the success of a retrenchment action is whether the given firm operates in the public vs private sector (Boyne & Meier, 2009). Finally, Barker and Mone (1994) argue for a potential reverse causality between retrenchment and turnaround. That is, whether to view retrenchment as the consequence of a decline in performance or the cause of a corporate turnaround.

2.5.3.2 How intense defensive actions?

In general, the consensus among researchers seems to be that relatively extreme cost-cutting retrenchment actions are to be preferred (Schweizer, 2017). Bruton et al. (2003) postulate that a firm's turnaround potential is a function of the magnitude of the retrenchment actions. Denis and Rodgers (2007) support this conjecture by linking the severity of reductions in assets and liabilities while the given firm is in Chapter 11 of the U.S. Bankruptcy Code to the likelihood of emerging as a going concern. Contrarily, Sudarsanam and Lai (2001) posit that firms in which retrenchment actions are more intense have a lower predisposition of successful recovery. They argue that this is due to an ineffective implementation of the retrenchment actions rather than the actions themselves.

2.5.3.3 When to act?

Having discussed which defensive actions to undertake during retrenchment and to what extent the intensity of such actions is desired, the question of timing of these defensive actions naturally emerges. The general consensus among scholars seems to be that the sooner the better (Moulton & Thomas 1993; Sheppard 1994; Jansen 2004). The research on this matter builds on the threat rigidity theory which can be summarized as the argument that low firm performance entails restricted information processing, centralized decision making, and most notably, increased organizational rigidity (Staw, Sandelands & Dutton, 1981). The imminent threat in question being that of corporate failure. In this regard, bigger firms may have a harder time implementing the necessary retrenchment strategies due to the organizational rigidity that accompanies firm size, thus resulting in a lower likelihood of experiencing a turnaround (Rosenblatt, Rogers & Nord, 1993; Audia & Greve 2006). Even for the case of smaller firms, some may likewise experience organizational rigidity due to low performance (Greve, 2011). Nonetheless, other authors present conflicting evidence. Van Witteloostuijn (1998) speaks for the opposite relationship between firm rigidity and chances of survival. He posits that high firm rigidity (i.e. high firm inertia) leads to a higher chance of survival of the firm. He explains this by the fact that inertia allows the firm to outlive its competitors. Similarly, Miller and Chen (2004) and Chattopadhyay, Glick and Huber (2001) find that firms which rush defensive actions also expose themselves to increased bankruptcy risk. Finally, Zajac and Kraatz (1993) draw on the resource-based strategy theory (Barney, 1991) and conclude that while some firms might experience a pressured need for retrenchment actions, they might not have the necessary resources to effectively implement such actions.

2.5.4 Recovery phase

Though a successful retrenchment phase is an important determinant of the given firm's probability of turnaround, the succeeding recovery stage is likewise paramount (Pandit, 2000). Again, the questions of what to do and when to do it emerge. Schmitt and Raisch (2013) specifically test the effectiveness of retrenchment actions in combination with recovery actions, relative to retrenchment actions only. They find that it is the combination of the two which yields a higher chance of experiencing a turnaround. Furthermore, Eichner (2010) posits that since recovery actions usually involve investments and growth-seeking opportunities, a successful retrenchment phase is needed in order to facilitate such liquidity-dependent recovery actions. Concretely, Hofer (1980) defines three stabilizing actions: product refocusing, market refocusing, and increase in market share. Despite these theoretical groundings, there is relatively little empirical support to be found in the literature. According to the thorough literature review by Schweizer and Nienhaus (2017), Sudarsanam and Lai presented in 2001 one of the only empirical backings regarding the effectiveness of recovery actions. Their study reveals that firms that continuously engage in "fire-fighting" actions do not recover, whereas growth-seeking and market-refocusing actions go hand in hand with successful recovery.

2.5.5 Empirical gaps in the literature

It is worth mentioning that the extant literature on turnaround research is highly biased in that most sample are collected from the Unites States or the United Kingdom. However, due to data availability described further in *3.* M*ethodology*, our paper does not contribute to closing this empirical gap in the literature.

Though inconclusive to a certain extent, our review of the retrenchment and recovery literature seems to point out a balance between initial severe short-term strategies and a subsequent reorientation with longer term future prospects in sight. Altogether, this suggests that the timing of the given strategies is of the utmost importance with regards to their effectiveness. To understand which specific covariates might help us predict the occurrence of turnarounds, we now proceed to a thorough review of the literature on key predictors.

2.6 Variables

In this section, we will present the variables that have been examined in the extant literature. Inspired by Schweizer and Nienhaus (2017) we will split the variables into the following categories:

1. Operational restructuring
2. Changes in the management
3. Portfolio restructuring
4. Financial restructuring
5. Underlying distress causes
6. Other control variables

2.6.1 Operational restructuring

Operational restructuring refers to changes regarding *how* operations are done, and not *what* is done. It therefore refers to changes in the operating efficiency rather than the operating strategy (Schweizer & Nienhaus, 2017). A textbook example of operating restructuring would be to look at Toyota. Operational restructuring would refer to Toyota applying the lean manufacturing model to their operations. In contrast, a strategic change would be Toyota moving from petrol cars to electric cars.

2.6.1.1 Operational processes

Changes in organizational processes are mainly manifested as a qualitative variable and have a low observability. For this reason, operational processes as a variable has been largely neglected in the literature regarding corporate turnarounds (Schweizer & Nienhaus, 2017). However, the research that does exist points to process innovation having a positive impact on the survival of firms. Sihna and Noble (2004) show that adopting new manufacturing technologies has a sizeable impact on firm survival. The same study also shows that it is of great importance that the timing of adoption is correct. An adoption which is made too late will wipe out the competitive advantages gained and therefore the effect on firm survival will vanish. The importance of timing is confirmed by Sudarsanam and Lai (2001).

2.6.1.2 Product innovation

As with operational processes, product innovation is difficult to observe and quantify on a large scale. The variable will not be used in our model, but former research has shown that the stage of a products' life cycle is important when determining how the introduction of the product will affect the general success of the company (Agarwal, Sarkar, & Echambadi, 2002). Other researchers have confirmed the role of product innovation during corporate distress, as innovation allows for an innovation premium to be charged by the company which improves the survival probability (Schweizer & Nienhaus, 2017).

2.6.1.3 Human capital

The effect of downsizing on firm performance is quite extensive. However, when comparing literature on the effect of downsizing on corporate turnaround, one must show caution (Schweizer & Nienhaus, 2017). Much of the literature does not take into consideration the health of the companies when measuring the impact of the organizational change on the subsequent financial performance. It is also important to take into account that unions, governments and public perception have a large influence on the decision to downsize a company's workforce.

Due to the aforementioned factors, the literature has shown different and contradicting results (Schweizer & Nienhaus, 2017). The positive effect of downsizing is the immediate cost saving that it provides. Love and Nohria (2005) show that the positive effect of downsizing requires a certain amount of slack in the workforce. On the other hand, alternative research has shown that an increase in the percentage of personnel being downsized results in an increased likelihood of bankruptcy (Norman, Butler, & Ranft, 2012). These contradictory findings could point to the fact that the effect of downsizing on corporate turnaround is dependent on other firm characteristics and cannot be said to have a strictly positive or negative impact.

2.6.1.4 Capital expenditures

Changes in capital expenditures (CAPEX) are in this paper defined as an operational restructuring. CAPEX refers to changes in how existing resources are utilized and does not include fundamental strategic changes in assets (Schweizer & Nienhaus, 2017). Changes in assets will be elaborated on in *2.6.3 Portfolio Restructuring*.

The current literature on the effect of changes in CAPEX is inconclusive. Furrier, Pandian and Thomas (2007) argues that CAPEX has a negative effect on turnaround in the early stages of financial distress and a positive effect in the later stages. However, it should be mentioned that the calculations of Furrier et al. (2007) only yield statistical significance when testing the impact on the early stages and not the later stages. In Sudarsanam and Lai's (2001) paper, the authors find no statistically significant impact of changes in capital expenditure on turnaround.

Similar to human capital, the positive effect of changes in CAPEX seems to be contingent on changes in other factors. The literature argues that changes in CAPEX need to be combined with asset retrenchment and portfolio restructuring, which is explained later in this chapter (Schweizer & Nienhaus, 2017).

Lastly, changes in capital expenditure as a managerial decision, might not always be available. During the financial crisis, 86% of CFOs in distressed companies argued that they did not have the opportunity to increase CAPEX to invest in attractive projects due to financial constraints (Schweizer & Nienhaus, 2017).

2.6.2 Managerial changes

Variables that concern changes in the managerial status quo of a company can be split into three sub-categories: CEO exchange, changes to the top management and changes in the board of directors.

2.6.2.1 CEO exchange

There is a general consensus in the literature towards CEO changes having a positive impact on the subsequent performance of the company.

Weisbach's (1987) research shows that announcements of a CEO resignation has a positive effect on corporate turnaround, when using stock returns as a measurement of turnaround. This is further underpinned by a range of other studies (Schweizer & Nienhaus, 2017). The strictly positive effect of changes in CEO was contradicted by Chen and Hambrick (2012) who show that changes in the CEO of the company has no impact on the subsequent performance of the company, when using ROE and market-to-book as performance measures. However, they did find CEO change to have an impact when combining the variable with a measure of the CEO's level of talent. Using the monthly return of the 4 years leading up to the firm's initial performance problems, Chen and Hambrick show that there is indeed a positive effect of removing a CEO with a low level of talent and a negative effect of removing a CEO with a high level of talent.

2.6.2.2 Changes in other top management positions

Looking at changes in the CEO should be complemented with examining the effect of changes in other top management positions, since merely focusing on the changes in CEO does not capture the full impact of management changes (Schweizer & Nienhaus, 2017).

On one hand, the research shows that the amount of pre-decline top management who stays with the company is related to the probability of corporate turnaround. On the other hand, scholars have pointed to the fact that there are a lot of other factors affecting the choice to keep or change the top management.

Sticking to the same top management could depict the company as a stable and credible firm, which should have a positive effect on the stock (Schweizer & Nienhaus, 2017).

2.6.3 Portfolio restructuring

Portfolio restructuring describes strategically motivated changes in a company's portfolio. While operational restructuring referred to changes which improve efficiency and liquidity, portfolio restructuring aims to refocus the business. There is a wide consensus in the literature that portfolio restructuring is an integral component of corporate turnaround (Schweizer & Nienhaus, 2017).

2.6.3.1 Divestments

Divesting part of the company's asset portfolio has been shown to have a positive impact on the likelihood of turnaround. In Denis and Rodgers' (2007) study of firms that file for Chapter 11 reorganization bankruptcy, the authors find that companies which significantly reduce their assets and liabilities while in Chapter 11 increase their likelihood of emerging from Chapter 11 as independent entities. Additionally, they find that the divestment has a positive relationship with the likelihood that the company will have a positive industry-adjusted operating margin in the 3 years following the reemergence from Chapter 11.

2.6.3.2 Investments

Only focusing on decreasing the amount of assets is, according to Schweizer and Nienhaus (2017), a one-sided strategy, which will make the company more prone to crisis. This ambiguity in whether a company should focus on divestments or investments is supported by the findings of Morrow et. al (2007). In their study of 178 single-product manufacturing firms, they find a significant relationship between increases in new products and a company's performance relative to its peers. These increases in new products will usually stem from an increase in investments in research and development or assets that allow for the production of new products. In the same model, Morrow et al. (2007) find a positive and significant relationship between the amount of assets a company owns and its performance compared to its peers. However, a relationship is also found between increases in divestments and performance. With results like these in the literature, it can, once again, be difficult to conclude on a general effect of portfolio restructuring. However, the research just mentioned finds a way around this by running a model, which has two variables that describe new products. One describing whether a new product has been introduced, and one describing whether a new product is valuable and difficult to imitate. By introducing this sub-variable, the model shows that the positive effect from introducing a new product stems from the products which create a competitive advantage. What this tells us about the issue of contradicting literature regarding divestments and investments is that one of the reasons for this ambiguity is the lack of differentiation in variables that will show what the money is spent on. Which assets are added and which are removed?

According to Schweizer and Nienhaus (2017) the existing literature supports the idea that the effect of portfolio restructurings is highly affected by the focus of the restructuring. Announcing that the company is going to refocus its strategy through a restructuring of its assets, is usually well-received by shareholders. However, if a company is critically distressed, the investment-part of the restructuring process might add more financial constraints on the company, which in turn will reduce the agility of the company.

2.6.4 Financial restructuring

Financial restructuring in connection to the likelihood of experiencing a turnaround can be split into two main categories. Debt restructuring and liquidity improvements (Schweizer & Nienhaus, 2017). Liquidity improvements include working capital optimization, dividend cuts or equity issuance. As to not confuse two categories of variables, changes in working capital will not include alterations of production processes, since this is part of operational changes (Schweizer & Nienhaus, 2017).

2.6.4.1 Debt restructuring

A lot of tax benefits can be gained from increasing the leverage of a company. Despite this, the amount to which different companies use leverage in their financial structure differs widely. One reason for this can be attributed to the default risk associated with levering the company (Molina, 2005). The fact that changes in capital structuring affect the probability of default and turnaround is widely agreed upon in the literature (Schweizer & Nienhaus, 2017).

A reduction in the leverage ratio has shown to increase the performance of companies that are highly leveraged. In a study of ski hotels from 2012 (Giroud, Mueller, Stomper, & Westerkamp), it is found that lowering the debt to equity ratio when in distress improves the performance of the company. All the changes in debt structure in this study stem from a reduction of debt (forgiveness) and not from an increase in equity. Supporting this is an article by Zingales (Zingales, 1998) which shows that high leverage results in less agile companies, which in turn results in higher probabilities of distress when a shock is introduced into the industry in which a company operates. Once again though, the literature is contradictory, as other scholars have found that high debt ratios result in improvements in operating performance. Indeed, companies experiencing successful turnarounds have a higher leverage ratio than their peers (Schweizer & Nienhaus, 2017). A proposed reason for the contradictions in the literature is the fact that most articles are focused on a very narrow industry field. Two examples would be Giroud et al. (2012) and Zingales (1998) whose samples are focused on ski-hotels and trucking companies respectively.

2.6.4.2 Liquidity improvements

Once again, the extant literature does not agree on the effect of changes in liquidity (Schweizer & Nienhaus, 2017).

In a study of the efficiency of turnaround strategies in small firms Chowdhury and Lang (1996) showed that companies who manage to complete a turnaround have more accounts payable than companies which do not complete a turnaround. Additionally, they show a positive connection between stretching accounts payable and the likelihood of turnaround (Chowdhury & Lang, 1996). Dividend cuts to improve liquidity are also shown to increase the likelihood of turnaround, however, at the same time, dividend cuts are often interpreted as a negative signal by investors and other stakeholders (Schweizer & Nienhaus, 2017). This means that the impact of dividend cuts might depend on whether the definition of turnaround is based on stock performance and returns or company financials.

When an increase in liquidity comes from an infusion of capital by an acquiring parent company, it has been found to have a negative effect on the operating performance of the company and therefore reduces the likelihood of turnaround (Gastrogiovanni & Bruton, 2000).

2.6.5 Underlying distress causes

The cause of the distress and whether it is internal or external is one of the most researched variables when it comes to predicting/modelling corporate turnaround (Schweizer & Nienhaus, 2017). The reason for this is that many scholars argue that the strategy used to exit distress and perform a turnaround should be very dependent on the reason for the distress. The underlying distress causes can be split into two main categories: external and internal causes of distress. External causes of distress are causes that are not directly influenced by management decisions. A typical example of this is industry decline. The general business cycle within an industry is most often independent of a single company’s management decision. This paper largely ignores the underlying distress causes due to a focus on other variables. This can be viewed as a limitation, or a potential improvement of the findings presented later. Additionally, as our distress definition is relative to the market, external distress causes that affect all companies in the market equally, will not affect the classification of distressed vs. non-distressed companies.

2.6.6 Other control variables

The control variables included in analyses that focus on turnaround differ slightly from research paper to research paper. However, there are a number of variables which are more typical than others.

Size of the company is used in a very large number of the research papers as a control variable. It is most often measured as the log of the assets of a given company (Molina, 2005; Denis & Rodgers, 2007). An alternative, less common way of measuring size is the log of sales (Chen & Hambrick, 2012). The implications of size on turnaround probabilities were commented on previously in this paper in *When to act?*

Another commonly used control variable is profitability. The measure of profitability does not seem to be agreed upon in the literature. Different examples are the return on equity divided by the market to book value of common equity (Chen & Hambrick, 2012), operating income divided by total assets (Molina, 2005; Denis & Rodgers, 2007), and net income over market value of total assets (Campbell, Hilscher, & Szilagyi, 2008).

The third commonly used control variable is a risk-measure, usually some sort of volatility. Examples of this include Campbell et al. (2008) who use three months annualized daily stock volatility, another example is Molina (2005) who uses income volatility as control variable.

Other control variables include a leverage ratio, liquidity measures and retained earnings as mentioned above, but also age and year dummies (Giroud, Mueller, Stomper, & Westerkamp, 2012; Furrier, Pandian, & Thomas, 2007; Morrow, Jr., Sirmon, Hitt, & Holcomb, 2007)

As mentioned several times above, the impact of many of the variables that have been examined in the literature is inconclusive when only looking at the variable. Many of them need to specified either qualitatively or through timing of the changes in the variables. Due to the fact that the sample size in this paper is 659,846, which is greater than the usual sample size in similar papers, we will refrain from using qualitative variables. Instead, we are going to focus on the timing of the changes in relevant variables compared to when the company went into distress. An example of this is the change in assets. In our analysis of the effect of changes in assets on the likelihood of turnaround, we split the assets into 4 timings. Changes in assets for the first six months, changes in assets from month 6 to 12, changes in assets from month 12-18 and finally changes in assets from month 18-24. This allows us to more closely examine the impact of the timing of the reaction to financial distress and should limit the ambiguity of the effect of the changes.

2.7 Capital asset pricing model

Having reviewed the literature on failure and turnaround, we turn to address relevant portfolio theory that will serve when evaluating the returns of our investment portfolios generated in *4. Analysis & Results*. The capital asset pricing model (CAPM) was originally devised by William F. Sharpe (1964), who argued that a simple model could be constructed and would allow for the valuation of stocks, dependent on their risk.

The CAPM model relates expected excess return of an asset and its systematic risk (β) through a linear relationship. The systematic risk describes how much the excess return of the asset varies with the excess return of the market in general. The excess return is calculated as the return of the asset R_i minus the risk-free return R_f. The last component of the framework is the rate of return of the market (R_m). The model is described as follows.

$$R_i - R_f = \beta(R_m - R_f)$$

Assuming the underlying assumptions of the CAPM are fulfilled (see Brealey et al., 2019 for a detailed description of the assumptions), then the rationale is that investors can diversify away all of the non-systematic (or project-specific) risk. Thus, the CAPM relates the return on an asset only to its sensitivity to the market (i.e. systematic risk) as expressed by the beta (Myers, Brealey, & Allen, 2019), as investors should not be compensated for non-systematic risk.

2.8 Cross sectional explanations for stock returns – a three-factor approach

Kenneth French and Eugene Fama have extended the CAPM to include a number of additional factors (Fama & French, 1996). Fama and French came up with a three-factor model, which was created to address a number of issues with the CAPM that had been pointed out subsequent to its development. The CAPM did a poor job at explaining (1) returns in relation to company size, (2) the fact that short term returns tend to continue, (3) the relationship between returns and book-to-market value of a company, as well as several other relationships between company financials and observed stock returns (Fama & French, 1996).

The three-factor model extends the already known CAPM from the previous section in this paper. The two added factors are a size factor and a value factor. The size factor describes the difference between the return of a portfolio containing small stocks and the return of a portfolio containing large stocks. This factor will from here on be called SMB (small minus big). The second factor is a value factor. This factor describes the difference in returns between a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks. This factor will from here on be called HML (high minus low). According to Fama and French (1996), these two factors in conjunction with a factor describing the overall excess return on the market should be able to explain the return of a single stock. The relationship is as follows:

$$R_i - R_f = \beta_{R_m - R_f}\left(R_m - R_f\right) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + e_i$$

Here, R_i is the return of stock *i,* R_f is the risk-free return approximated by the one-month Treasury bill, R_m is the return on the market and $\beta_{(R_m) - R_F}$, β_{SMB}, β_{HML} are the factor loadings for the excess return on the market, SMB and HML respectively. e_i is the error term.

SMB and HML are constructed as follows. Fama and French (1996) use data from the COMPUSTAT and CRSP databases. They allocate all stocks from the NYSE, AMEX and Nasdaq into two groups. One representing small stocks (S) and one representing big stocks (B). The definition of whether a company's stocks constitute those of a big or a small company is a relative measure. If the market value of equity (ME) is below the median of all the stocks in the dataset, the stocks are allocated to the small group and if ME is above the median, they are allocated to the big group. The full dataset is then split up into three new groups based on their book-to-market ratio. The break points are as follows. The companies which are within the lowest 30% are in the low group (L), the companies that are in the middle 40% (i.e. between 30% and 70%) are allocated to medium (M) and the remaining companies in the upper 30% are allocated to high (H). These subgroups can now be used to create six "size-book-to-market" portfolios. S/L, S/M, S/H, B/L, B/M and B/H are defined as the intersect of the three book-to-market groups and the two size groups (Fama & French, 1996). The value-weighted return of these portfolios is then calculated and used to construct SMB and HML. SMB is the difference each month between the average return of the three small portfolios (S/L, S/M, S/H) and that of the three big portfolios (B/L, B/M, B/H). HML is constructed similarly. The factor is calculated as the difference in average returns each month between the two high portfolios (S/H, B/H) and the two low portfolios (S/L, B/L).

Important to mention in regard to financial distress and turnaround is that Fama and French argue that the higher average returns of relatively distressed companies is captured in this model via HML. Relatively distressed companies usually have high book-to-market values and therefore load heavy on HML.

Fama and French (1996) find the three-factor model to better describe returns than the aforementioned CAPM in all tested scenarios and overcome most of the critique of the CAPM that has previously been voiced.

2.9 Cross sectional explanations for stock returns – a five-factor approach

Subsequent to the development of the three-factor model, researchers have found many anomaly variables. Put differently, variables that affect the return of companies but are not captured in the three-factor model (Fama & French, 2015). To overcome these shortcomings of the three-factor model, Fama and French (2015) extends their original model by adding two extra factors. One describing the profitability of a company and one describing the investments of a company. The extended model is as follows.

$$R_i - R_f = \beta_{R_m - R_f}\left(R_m - R_f\right) + \beta_{SMB}(SMB) + \beta_{HML}(HML) + \beta_{RMW}(RMW) + \beta_{CMA}(CMA) + e_i$$

The added components of this equation are β_{RMW}, RMW, β_{CMA} and CMA. RMW (robust minus weak) is the difference in returns on a portfolio of companies with robust profitability and a portfolio of companies with weak profitability. CMA (conservative minus aggressive) is the difference in returns between a portfolio of companies that invest little and a portfolio of companies that invest a lot. The beta values β_{RMW} and β_{CMA} represent the factor loadings of RMW and CMA (Fama & French, 2015).

RMW and CMA are constructed in the same way as HML in the three-factor model. The profitability factor RMW is constructed using operating profit and the investment factor CMA is constructed using changes in total assets from ultimo the fiscal year t-2 to ultimo the fiscal year t-1 (Fama & French, 2015).

The key result of Fama and French’s (2015) research is the finding that this model overcomes many of the challenges of the three-factor model. They also find that by including the two additional variables, HML becomes redundant. In this paper, we have chosen to use the five-factor model with HML instead of leaving it out. This is done, as we look at distressed stocks and the initial purpose of this variable by Fama and French was precisely to capture the additional return of relatively distressed stocks.

2.10 Performance measures

2.10.1 Investment alphas and stock returns

One way to investigate whether a portfolio generates abnormal returns is by looking at the investment alpha. To calculate the beta of the CAPM or the factor loadings in Fama and French's three-factor and five-factor models, regressions are used. To calculate the CAPM-beta of company XYZ, the excess returns of the stock is regressed against the excess return of the market. The same approach is used in the factor models but using more covariates. This approach is further explained in *8.4 Distress factor.* Should these regressions find an alpha different from zero, the models are not able to explain all of the excess return of XYZ (Fama & French, 1996). Using the three-factor model as an example, what this means is that the excess return of XYZ cannot be explained by its exposure to the three factors. The excess return does not stem from small companies having higher average returns than big companies, the exposure to the market risk or the fact that companies with high book to market ratios usually outperform low book-to-market ratio companies (Fama & French, 1996). Therefore, investors seek to find a positive alpha when evaluating their investment returns, since one explanation of the alpha could relate to the investors' abilities as a stock picker.

In this paper, we use investment alphas to investigate whether there are unexplained excess returns when either investing in or shorting relatively distressed stocks based on predicted probabilities of failure.

2.10.2 Sharpe ratio

The Sharpe ratio is in this paper used as a performance measure to compare different investment strategies. The Sharpe ratio builds on two measures, historic returns and historic volatility (Sharpe, 1994). The ratio is as follows:

$$\frac{R_{pf} - R_f}{\sigma_i}$$

, where R_{pf} is the return of the portfolio*,* R_f is the risk-free return, and σ_i is the standard deviation of the portfolio. According to Sharpe (1994) the Sharpe ratio does not cover cases in which only one investment return is involved. Effectively, the Sharpe ratio yields the return per unit of risk, which in turn can improve the process of managing decisions (Sharpe, 1994).

As already noted, the Sharpe ratio is used to measure and compare the performance of investment strategies in this paper. Alternatives to the Sharpe ratio is the *Treynor ratio* and *Information ratio.* We have chosen not to use the Treynor ratio, because the risk measure in this ratio (the denominator) is the

CAPM beta-value of the portfolio. As is shown in *Analysis & Results*, the CAPM performs very poorly when used to explain the returns of the assets this paper focuses on. Therefore, the beta-value produced by the CAPM is expected to be a poor descriptor of the risk of the assets. The Information ratio is based on a return of a portfolio relative to a benchmark. However, the second measure we use to determine the performance of the investment strategies is the five-factor model developed by Fama and French (2015). The factors in the five-factor model are based on several portfolios constructed to mimic the returns of small companies, large companies, companies that invest aggressively, companies that invest conservatively etc. For this reason, we argue that the alpha of this measure in itself allows us to compare the returns to a number of relevant benchmark returns, and the Information ratio therefore adds little value. The Sharpe ratio on the other hand completely ignores the benchmarks and only looks at the performance of the portfolio and therefore serves as a great supplement to the five-factor model.

3. Methodology

This chapter outlines the research design and justifies our methodological choices. Firstly, we address the scientific view used to delimit our methodological approach to answering the questions presented in the introduction. Secondly, we construct a solid base of explanatory and control variables based on the literature review and collect relevant data. Thirdly, we select the most appropriate measures for distress and turnaround with regards to our analyses. Fourthly, we address reasons for winsorization, interpolation, and other modifications to the data. Fifthly, we provide a thorough description of the logit-specification which will be used in our analyses. The considerations of each element will be explained in turn.

3.1 Scientific view

This paper and the knowledge in it is, as most research is, generated off and based on phenomena observed in reality. Such phenomena can be characterized by an underlying paradigm determining how reality is perceived. To delimit our methodological approach to answering the problems and questions presented in the introduction, the paradigm in which we work needs to be specified. Our approach to researching the topics in this paper relies heavily on dynamic logit models with a high number of observations. These models are based on historical observations of the covariates. Studying a large number of single observations as a means to answer a research question is known as induction, which is the main approach of this assignment. Looking at philosophical theories of research, the one most often connected to a strong focus on induction is *positivism* (Holm, 2018). The ontology of positivism is *realism*. What this means is that causal connections and phenomena studied are independent of the researchers, as they exist in reality (Egholm, 2016). The epistemology in positivism likewise suits this paper. Empirical research is the main approach to go about the induction due to the ontology just described. What can be empirically observed exists in the real world, while something that cannot be observed does not exist, and can therefore not be used to verify the research (Egholm, 2016).

In this paper, we work within the paradigms concerning *economics, finance* and *mathematics.* These paradigms each consist of *exemplars* and a *disciplinary matric* (Holm, 2018). Exemplars are the fundamental and foundational examples of why paradigm works, whereas disciplinary matrices are the foundational assumptions that are taken for granted within a paradigm. In this paper, the different disciplinary matrices contain, among other things, effective markets and the fact that historical observations can say something about future observations.

As we conduct scientific research, it is important to distinguish between *normal science* and *scientific revolutions* (Holm, 2018). We are not attempting to establish a new paradigm or cause a paradigm shift by changing the exemplars and/or the disciplinary matrices of the paradigms within which we work. However, even though we do not seek to nor accomplish scientific revolutions, our findings in this paper might add to the literature that questions the effective markets and have therefore started to test part of a disciplinary matrix.

3.2 Data collection

As mentioned in *1.5 Problem Definition and Approach*, our in-sample period of analysis runs from 1963 to 2004, while our out-of-sample period of analysis runs from 2007 to 2018. These periods refer to the raw data collection periods. However, for some of the analyses conducted in *4. Analysis & Results*, these time periods have been reduced due to our specifications of lagged variables and/or a lack of data points. An example is, that the investment strategies that are tested in *4. Analysis & Results* are only tested from 1973, due to a lack of data for years preceding 1973. Data have been collected from three sources: the Center for Research in Security Prices (CRSP) and COMPUSTAT, which both have been accessed via Wharton Research Data Services (Wharton - University of Pennsylvania, 2019). We collected all the data that were available in the databases. Our datasets should therefore encompass data that reflects the entire U.S. market, or at least approximatively. This said, when running our analyses later on, we cut some observations in order to have data points on all relevant variables in exactly the same periods. The explicit reasons and manipulations are presented throughout the analysis when relevant.

Additional data have been collected from Kenneth French's website (Kenneth R. French Data Library, 2019).

3.2.1 Stock prices, delisting codes, delisting amounts, S&P500 returns, S&P500 level

Data on stock prices, delisting codes, and delisting amounts were collected from the CRSP. Stock prices are available for securities traded on the NYSE, the AMEX, or the NASDAQ markets (Wharton - University of Pennsylvania, 2019) We collected data on all available companies. Furthermore, we collected historical returns on the S&P500 index as well as the total market value of the S&P500 index.

We collected monthly stock prices rather than daily, since we later needed to match the dates from financial statement data which are not available on a daily basis. Additionally, the number of companies that CRSP has daily data on is substantially lower than when looking at monthly data.

Delisting codes reflect the reasons why CRSP stopped collecting data on a given security. The delisting amount is the value of the issue used to calculate the ending value in the delisting return. It is the value of the issue at the time of delisting(Wharton - University of Pennsylvania, 2019). We use these delisting amounts in our investment portfolios when calculating portfolio returns for stocks that failed. For all other stocks, it is the stock price which is used when calculating portfolio returns.

Our replication of Campbell et al. (2008) further requires the construction of a variable EXRET which is computed as the monthly log excess return on each firm's equity relative to the S&P 500 index. Moreover, we will construct a variable RSIZE, a ratio in which the numerator is the market capitalization of the company and the denominator is the total market value of the S&P 500 index. We thus collect monthly S&P 500 returns and total market capitalizations for the sample period 1963-2005.

3.2.2 Fama and French five-factor model

When computing portfolio alphas, we control for the five factors set forth by Fama & French (2015). Monthly data on the factors (i.e. monthly risk premia) are collected from Kenneth French's website (Kenneth R. French Data Library, 2019). The five factors have been carefully described in *2.9 Cross sectional explanations for stock returns – a five-factor approach*.

The stock return is given in our sample, but the return on the market and the risk-free return are not. For the risk-free return, we see two viable options. We could either use the return on 10-year treasury bills or the risk-free rate provided by Kenneth R. French (Kenneth R. French Data Library, 2019). He uses the one-month Treasury bill rate as a proxy for the risk-free rate. For conformity purposes, it serves us to use the same risk-free rate as Kenneth French, since we are also using the values of his five factors, which are derived assuming that same risk-free rate.

Our selection of market return proxy likewise presents a few alternatives. We see three potentially viable options: Option 1 would be to use the S&P500 as a proxy for the market and then calculate the return on based on the level of the S&P 500. Option 2 would be to take all American stocks available in the CRSP database and calculate a value-weighted return based on this sample. The third option would be to use the market return provided by Kenneth R. French (Kenneth R. French Data Library, 2019). As we are using the variables provided by French in our regressions estimating the beta-values for our five-factor model and we want to have consistency between the variables used in the two models, we decided to use the variables provided by Kenneth R. French.

3.2.3 Financial statement data

We have collected data on fourteen financial statement items through the Compustat – Capital IQ database accessible via Wharton Research Data Services (WRDS).

On a quarterly basis, data were collected on total assets, cash and cash equivalents, total liabilities, net income, common shares outstanding, employees, total current assets, total current liabilities, debt in current liabilities, total long-term debt, total revenue, and interest expense.

On a yearly basis, data were collected on capital expenditures and cash dividends. Quarterly values would have been desirable (however, they were unavailable in large scale) since more data points and more fluctuations would yield more powerful logit models later on.

3.3 Our replication and Campbell et al. - main differences

Although we set out to start our paper with an exact replication of Campbell et al.'s (2008) analyses, we did not have access to the exact same data. In the following, we explain in what ways our replication slightly differs from the original analyses.

The first and main difference is that our definition of failure differs. We did not have access to the Kamakura Risk Information Services database, in which case we had to come up with a different measure of failure. Since Campbell et al.'s (2008) generated failure model covariates based on market prices collected from CRSP, we deemed it consistent to define failure on the basis of delisting codes collected from the same database (see more details on the specific delisting codes in *3.4.1 Failure measure*).

Secondly, Campbell et al. (2008) have managed to gather more data points from the CRSP and COMPUSTAT databases than we have. We have not been able to establish why, since we collected data on the all firms in the same databases. Besides thus having a lower number of observations in our failure model, this had a minor implication on our construction of the stock volatility variable SIGMA.

Thirdly, since the time when Campbell et al. (2008) did their three-factor study based on Fama and French (1996), Fama and French have later extended their model to include five factors, in which case we will rather use the updated model when evaluating our portfolio returns.

On a final clarifying note, the analyses presented in this paper does not end after the replication of Campbell et al. (2008). We further proceed with an attempt of enhancing the portfolio returns found in our replication by modelling probabilities of turnaround. More details will follow in *4. Analysis & Results*.

3.4 Measures of failure, distress and turnaround

The starting point of our analyses is to define the concepts of failure, distress, and turnaround. In the following, the conceptualizations will be discussed in turn, along with potential limitations.

3.4.1 Failure measure

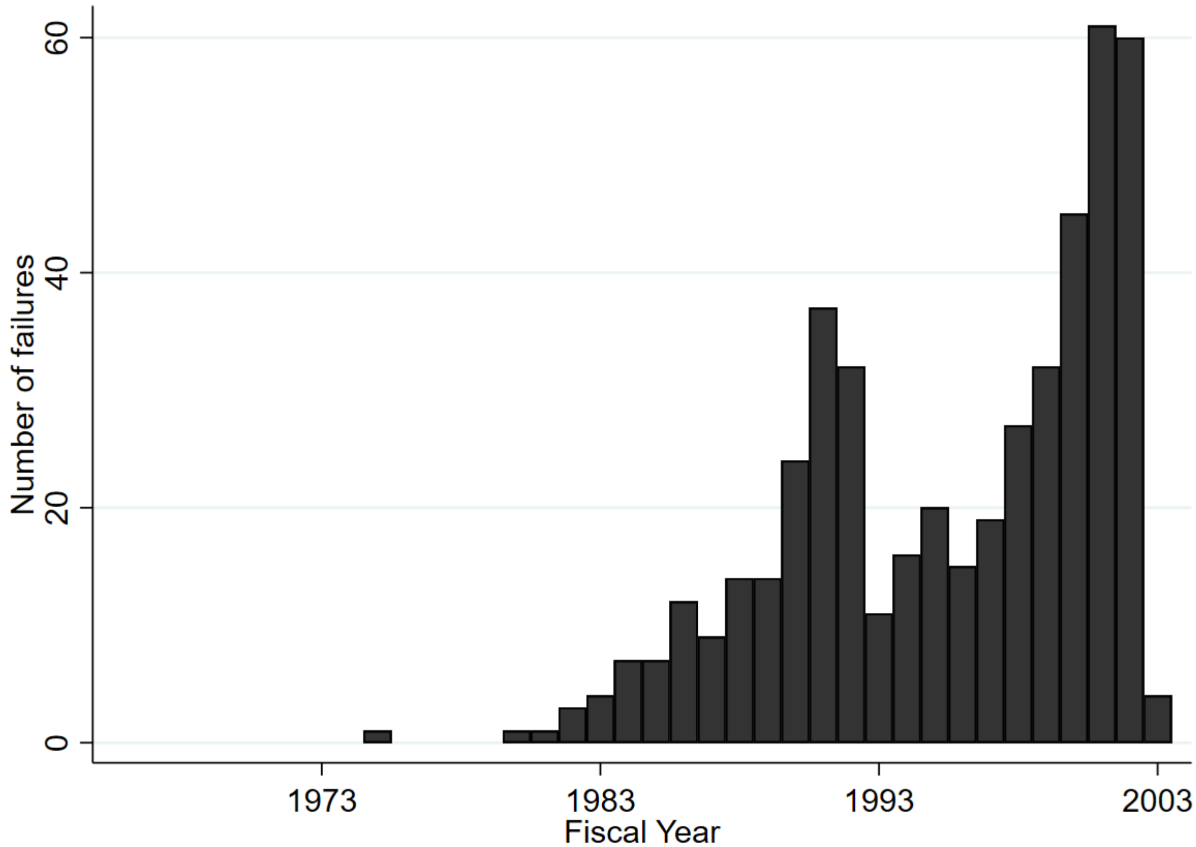
Based on the overall list of delisting codes (CRSP, 2019) we have narrowed down three codes which we believe correspond to failure:

- code 552 - “Delisted by current exchange - price fell below acceptable level”,
- code 560 - “Delisted by current exchange - insufficient capital, surplus, and/or equity”, and
- code 574 - “Delisted by current exchange - bankruptcy, declared insolvent”.

Although the selection process has been careful, we realize that this is a somewhat arbitrary choice. However, as mentioned in our literature review, most studies use an arbitrary measure of failure. As a proxy for failure, we thus define a dummy variable d_bankrupt which takes on 1 if the delisting code corresponds to 552, 560, or 574.

Throughout the sample period we have a total of 476 failures. Expectedly, most bankruptcies happened around the dotcom bubble (see Figure 2). There is also a peak in bankruptcies around 1990, which could be explained by political and economic instability. Regardless of the cause, this inspires a later robustness check in which we delimit the sample period in subsets in order to isolate the effect of crises.

Figure 2 – Number of corporate failures over the period 1973-2003



Note: This figure depicts the number of corporate failures over the period 1973-2003. It includes companies that were delisted by the Center for Research in Security Prices with one of the following delisting codes: 552, 560, or 574.

Source: Own computation based on data from the Center for Research in Security Prices (2019).

3.4.2 Distress measure

In *4. Analysis & Results*, we present the results of running a dynamic logit model on the aforementioned bankruptcy dummy variable and rank the stocks according to modelled probabilities of default. We define distressed stocks as those belonging to the highest decile (highest probabilities of default). In plain English, a company is in distress if it is among the 10% of companies that are most likely to fail in one year. This definition presents a couple of challenges which need to be addressed: (1) the choice of using 10% as the cut-off point and (2) the fact that the definition is a relative definition.

Even though the probabilities predicted using our failure prediction model are all relatively low compared to those predicted using Campbell et al.'s (2008) model, the top decile is at a significantly higher risk of failure than the rest of the companies when comparing the averages. Specifically, the average probability of the top decile is 29.4 times higher than the average of the rest of the observations. We therefore conclude that it is fair to state that the top decile of the observations is relatively more distressed compared to the rest of the observations.

Moreover, to investigate the impact of our arbitrary cutoff point, we considered the argument that the highest decile might be relatively more volatile than say, the highest percentile. That is, stocks might 'compete' to be amongst the 10 percent highest probabilities of default, whereas the 20 percent highest probabilities of default belong to a relatively constant pool of firms. This issue is investigated in a robustness check in *4. Analysis & Results*.

The second potential issue with our definition of distress is that of relativity. As our definition is a comparison of the risk of a single company to the risk of the general market, it is relative and therefore has a number of pitfalls that should be pointed out. First of all, the number of distressed companies will always be predetermined. For instance, when using the top decile as a cutoff point to define distressed firms, this will always classify ten percent of the total number of companies as distressed. This is not realistic, as it is to be expected that the number of distressed companies varies over time. Take for instance the period 2000-2010. It is fair to assume that a larger percentage of the total number of companies were in financial distress in the later part of this period due to the financial crisis. This variation in overall distress risk would not be observable when using our definition. Secondly, when using a relative definition, some companies will stop being financially distressed, just because another company suddenly is more distressed. This is the biggest limitation to our definition and it will be further addressed once the model has been developed.

3.4.3 Turnaround measure

As we are modelling turnaround for financially distressed companies, the turnaround definition is strictly dependent on the definition given above of financial distress. Turnaround can be defined as occurring when a financially distressed company manages to leave the riskiest decile of the market. Due to the interdependence of the definitions of distress and turnaround, the same limitations can be argued for the turnaround definition as those argued above for the distress definition.

An important feature of our selected dependent variable of our turnaround prediction model should be noted: Exploratory regressions suggested much better explanatory power when the dependent variable was defined as turnaround happening *within* the following twelve months rather than happening *exactly* twelve months from now. We therefore defined the dependent variable of our turnaround prediction model as 1 if turnaround happened withing the following twelve months and 0 otherwise. This choice is also in line with our interest in utilizing the turnaround probabilities in an investment strategy, which is restructured only once per year. At each restructuring, we are interested in selecting the companies that have the highest probability of performing a turnaround before the next restructuring of the portfolio.

According to our third hypothesis set out in the Introduction, an investment strategy, that focuses its stock-picking on distressed stocks can be improved if the selection of stocks for the portfolio is assisted by a measure of the firm's probability of experiencing a turnaround. We will therefore investigate whether a turnaround model can positively impact the investment strategy (presented in *4. Analysis & Results*) that involves going long in distressed firms (L90). Due to this interest, our turnaround definition purposely does not specify how long a company has to stay non-distressed. As described in *2. Literature Review*, previous studies have incorporated such criteria into their definition to exclude cases where a company has turned around only to see it fall back into distress the very next period. This is a legitimate concern, however, as the investment portfolio in L90 is restructured every January (by construction), this is not relevant to our definition. Our assumption is that if a company leaves a state of distress, this is mirrored in the price change of the stock. The same would be true in the next period, if the company would fall back into distress. In the first period, the price increases and in the second period it decreases again. For L90 the situation would look as follows: In period 0, the company is in a distressed state, and it is therefore part of the investment portfolio. In period 1 it has left the distressed state (performed a turnaround according to our definition), and the stock is sold off at a profit, due to the increase in price. In period 2, the company once again becomes distressed and is therefore bought back. However, it is bought back at a lower price than it was sold for, due to the decrease in price described above, and the profit of the turnaround has therefore been captured. The alternative example would be a long-term investment strategy, where the portfolio would only be restructured every five years. This portfolio would not have made a profit from the turnaround. Therefore, had we wished to test whether a turnaround model could be used to improve such an investment strategy, we would have to include a time element into our definition of turnaround

3.5 Data manipulation

Before conducting our analyses, we prepare the data by constructing new variables, winsorizing when needed, among other things. All these manipulations are discussed in turn. Note that all of our data manipulations and analyses in this paper are conducted using the statistical software Stata 15. Note also that all logit regressions have been run with Stata's in-built option 'robust', which allows us to compute standard errors that are robust to some kinds of misspecification (Harrell, 2015).

3.5.1 Preparing data

3.5.1.1 Data collection error

The stock prices which we collected from CRSP exhibited strange patterns. What first alerted us was the surprising amount of negative prices which does not make much sense. A price should be either positive or null. Otherwise it would mean that you receive money for investing in a stock rather than paying for your investment in it. Detailed summary statistics for raw stock prices are presented below:

Figure 3 – Summary statistics of raw stock prices

```
                   Price or Bid/Ask Average
-------------------------------------------------------------
      Percentiles      Smallest
 1%      -34.25           -628
 5%       -15.5       -458.125
10%          -7           -401       Obs           1,802,729
25%     1.96875           -385       Sum of Wgt.   1,802,729

50%     10.8125                      Mean           13.86496
                       Largest       Std. Dev.      23.94075
75%       23.24        1049.95
90%       38.25           1090       Variance       573.1595
95%        50.5        1097.02       Skewness       4.179483
99%          85        1099.99       Kurtosis       95.84685
```

Note: This figure presents detailed summary statistics of raw stock prices, computed as the average between the ask and bid prices.

Source: Own computation based on data from the Center for Research in Security Prices (2019).

When browsing the data, it seemed as though prices sometimes randomly were multiplied by minus one. To depict a common pattern that we saw, see Figure 4.

Figure 4 – Sample extract of the suspicious patterns in the evolution of stock prices

19981130	AABC	-6.8125
19981231	AABC	7.25
19990129	AABC	7
19990226	AABC	-7
19990331	AABC	7
19990430	AABC	-7.8125
19990528	AABC	7.375
19990630	AABC	7.8125
19990730	AABC	7.875
19990831	AABC	8.375
19990930	AABC	8.3125
19991029	AABC	8
19991130	AABC	7.8125
19991231	AABC	7.9375
20000131	AABC	-7.703125
20000229	AABC	-6.59375
20000331	AABC	5.9375
20000428	AABC	5.625
20000531	AABC	-6.28125

Note: This figure represents the evolution of stock prices for a randomly chosen extract of our total sample. It highlights suspicious patterns in the data and concerns the firm AABC over the period 30.11.1998-31.05.2000.

Source: Own computation based on data from the Center for Research in Security Prices (2019).

Assumingly, an error has occurred in the data. We thus choose to multiply the negative prices by minus one in order to render our price data useful for further analyses. Note that Campbell et al. (2008) do not mention such alteration of their price data. If they did not readjust prices accordingly, this could be an additional driver of differences between their results and ours.

3.5.1.2 Readjusting book values of equity and assets

In accordance with the analyses of Campbell et al. (2008) we readjusted our book values of equity and book values of assets in order to deal with outliers. The reason why we are particularly interested in adjusting the book values of equity and assets is that we later use these values as denominators in the calculation of several ratios. Thus, if the values are uncommonly small (most likely due to mismeasurements), this would yield abnormally high ratios. Therefore, we adjusted asset values by adding ten percent of the difference between market and book equity to the book value of total assets.

We conducted a similar adjustment with the book values of equity. That is, we added ten percent of the difference between market and book equity to the book value of equity.

$$Total\ Assets\ (adjusted)_{i,t} = TA_{i.t} + 0.1(ME_{i,t} - BE_{i,t})$$

Here, $TA_{i,t}$ represents the total assets before adjustment of company *i* at time *t.* ME is the market value of equity and BE is the book value of equity.

Note that these adjustments are preliminary, and that we also proceed to winsorize the data later which will further deal with the presence of outliers. This is discussed in more detail later in this chapter.

3.5.1.3 Merging data dates

When merging data from the three different sources, we had to match the dates from the different data sets. Some of the data were values as of the end of a month, while other data were values as of the beginning of a month. We assembled all the data so that they matched the end of the month. All data that were matched on dates were forwarded in order to make sure that the information the variables provided was available at the date they were moved to. As an example, say our observations are on 30th of June and the 31st of July, and we have a variable book-value of equity, that for some reason has the date 5th of July. This observation of book-value of equity will then be pushed to the 31st of July, instead of 30th of June as this date is closer to the real date, 5th of July. However, if we move the observation to the 30th of June, the information that book-value provides will occur earlier in our dataset than it did in real life. We will therefore have an observation that has information, which was not available at the time.

To make sure that observations were matched both on the date and firm, we generated a unique identifier DATETIC as the contraction of date and ticker symbol. For instance, ultimo January 1963, the firm which has the ticker symbol "A" would have a DATETIC equal to "A19630131".

Roughly one percent of our collected data was expressed in Canadian dollars (CAD), while the rest was denominated in US dollars (USD). For comparability purposes, we dropped data with values denominated in CAD. Alternatively, we could have collected historical exchange rates and converted the CAD into USD. However, this concerned only a small portion of our data and we preferred to restrict our analysis to the market of the United States.

3.5.1.4 Monthly to yearly returns

As previously described, we collected *monthly* data on the factors of the Fama-French five-factor model as well as the risk-free rate. However, as we want to compute *yearly* portfolio returns as of the end of January (see *4. Analysis & Results*), we calculate the one-year accumulated returns on the five factors and the risk-free rate. Using SMB as an example, it is computed as follows $(1 + smb_{t+1}) * (1 + smb_{t+2}) * \ldots * (1 + smb_{t+12}) - 1$ where t is the current period described in months. Note that we start at t+1 instead of t because of the way the data from Kenneth French's website (Kenneth R. French Data Library, 2019) and our data line up on dates.

3.5.2 Construction of additional explanatory variables

We need two sets of variables: one for our failure prediction model, and one for our turnaround prediction model. Before constructing the additional variables, we interpolate monthly balance sheet data from the quarterly values.

3.5.2.1 Interpolation of financial statement variables

As described in *Data collection*, we have collected monthly data on stock prices, delisting codes, delisting amounts, risk-free rate, and the five Fama-French factors. However, financial statement data is quarterly at best. Thus, we have two options: (1) to use only data for which we have values for all variables or (2) interpolate monthly financial statement data from the quarterly values. The problem with (1) is that we have much fewer observations to run logit models with. The problem with (2) is inaccuracy in interpolation. Without explicitly expressing it, Campbell et al. have selected option (2). Thus our replication will likewise include simple interpolation of financial statement data. Since we have no other information about the firms, our best predictor of next months' financials are this month's values. For instance, the first quarterly value of total assets is stated in January. The variable total assets then takes on the same values in January, February and March. When a new quarterly financial statement is released in April, that value is then extended to May and June. And so on. This interpolation triples the amount of data points at the cost of likely inaccuracies in the data gained from financial statements.

3.5.2.2 Failure prediction model explanatory variables

Now possessing monthly data for all our raw variables of interest, we turn to compute additional explanatory variables. For the failure prediction model, we construct the same variables as Campbell et al. (2008). They got inspiration in their choice of variables from Shumway (2001) but did some important modifications. Notably, they use market values of assets rather than traditional accounting values.

3.5.2.2.1 Market value of assets

The main advantage of using the market value of total assets rather than the book value is that it is adjusted on a monthly basis rather than quarterly (through monthly changes in the market value of equity). Thus, this measure captures more information than the plain book value of total assets (see also our discussion of failure prediction models in *2. Literature review*). In accordance with the variable definitions of Campbell et al. (2008), we define MTA as the market value of total assets

$(\text{market value of equity} + \text{book value of total liabilities})$. The market value of assets in our data is calculated as $\text{common shares outstanding} * \text{stock price}$.

3.5.2.2.2 Profitability ratios

To carry on with the construction of failure prediction model covariates, we generate NIMTA defined as net income divided by the market value of total assets. Rather than simply using the ratio of net income to market value, we impose declining weights on the lagged values. This is done to capture the fact that a consistent decline in the ratio is a better predictor of failure than a sudden one-off decline. NIMTAAVG is then computed as a twelve months weighted average of NIMTA with the most recent months weighing the most. Phi represents the weight that is imposed on lagged values of NIMTA and takes on the value $2^{-\frac{1}{3}}$. This can be interpreted as a weight that becomes reduced by half each quarter.

$$NIMTAAVG_{t-1\,,t-12} = \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{t-1\,,t-3} + \cdots + \phi^9 NIMTA_{t-10\,,t-12}$$

Similarly, we generate the geometrical average excess stock returns as:

$$EXRETAVG_{t-1\,,t-12} = \frac{1-\phi}{1-\phi^{12}}(EXRET_{t-1} + \cdots + \phi^{11} NIMTA_{t-12}$$

, where EXRET is the monthly log excess return on each firm's equity relative to the S&P 500 index. In the same spirit, a consistent decline in the monthly excess returns is more likely to explain failure than a sudden one-off drop in stock price.

3.5.2.2.3 Leverage ratio

We define TLMTA as the total liabilities divided by the market value of total assets. This measure captures the capital structure of the firm. A highly geared firm is more likely to experience a failure to meet its financial obligations than a lowly geared one. This is simply due to the inherent seniority in the bankruptcy structure when financed with debt versus equity (Myers, Brealey, & Allen, 2019).

$$TLMTA_{i,t} = \frac{Total\ Liabilities_{i,t}}{Firm\ Market\ Equity_{i,t} + Total\ Liabilities_{i,t}}$$

3.5.2.2.4 Liquidity ratio

We next compute CASHMTA defined as cash and short-term investments divided by the market value of total assets. Motivated by the current literature on financial flexibility within capital structures, CASHMTA will reflect the firm's liquidity position. Ceteris paribus, it is expected that a firm with a strong liquidity position could more easily avoid bankruptcy than a firm with a poor liquidity position.

$$CASHMTA_{i,t} = \frac{(Cash\ and\ Short\ Term\ Investments)_{i,t}}{Firm\ Market\ Equity_{i,t} + Total\ Liabilities_{i,t}}$$

3.5.2.2.5 Market-to-book ratio

We define MB as the market-to-book ratio. This ratio is commonly used to depict the market's perception of a firm's value. Since our liquidity-, leverage-, and profitability ratios all use market values of total assets; any unexplained variation accreditable to the book values of total assets could be picked up by the MB ratio. In that sense, the variable could correct for implausibly high MB ratios by increasing the probability of default.

Inspired by Shumway (2001), we finally generate RSIZE and SIGMA as covariates. RSIZE captures the impact of size on default probabilities. Based on our review of the extant literature and common economic intuition, we would expect bigger firms to have lower probabilities of default, as they have more potential to downscale than relatively smaller firms.

$$RSIZE_{i,t} = \log\left(\frac{Firm\ Market\ Equity_{i,t}}{Total\ S\&P500\ Market\ Value_t}\right)$$

Our calculation of SIGMA differs slightly from that of Campbell et al. (2008). They use daily stock returns to compute annualized three-month rolling sample standard deviations as a proxy for stock return volatility. However, we tried this, but it significantly reduced our amount of observations. That is because CRSP provides monthly observations on many more firms than it does for daily observations. Thus, we recognize the limitation, and decide to compute SIGMA on the basis of monthly observations instead. Since we cannot use daily data, we extend the window from a three-month rolling window to a twelve month rolling window in order to have more than three observations to calculate SIGMA. The monthly stock volatility is then annualized.

$$SIGMA_{i,t} = annualized\ sd = \sqrt{12} * \sqrt{\frac{1}{t-1}\sum_{i=1}^{t}\left(return_{i,t} - \overline{return_{i,t}}\right)^2}$$

3.5.2.3 Turnaround prediction model explanatory variables

Before modelling turnaround probabilities, we develop a few additional covariates. In the following, we only mention the covariates which enter into our final turnaround logit model (in *4. Analysis & Results*, we elaborate further on other potential covariates which we investigated):

3.5.2.3.1 Liquidity

First, the current ratio as defined by the current assets divided by the current liabilities. The current ratio captures the firm's ability to finance its short-term obligations using short-term assets. Hence a higher current ratio is expected to be met with a higher probability of turnaround, ceteris paribus.

We also define a variable which captures the change in current ratio from one period to the next using intervals of six months.

3.5.2.3.2 Leverage

Second, the debt composition as defined by the debt in current liabilities divided by the total debt. This variable captures the extent to which the firm is financing its operations using short-term debt rather than long-term debt. One would expect that more short-term debt pressures the firm and thus diminishes its chances of experiencing a turnaround.

We also define a variable which captures the change in debt composition from one period to the next using intervals of six months.

Third, the short-term debt divided by total market value of assets captures what proportion of total assets is financed with short-term debt. Short-term debt being more pressing and expensive than long-term debt, one would expect that a high short-term debt to assets ratio would yield lower probabilities of experiencing a turnaround.

These measures of leverage ratio as well as TLMTA described above are expected to have some correlation. This correlation and its effect on the final turnaround prediction model is commented on later in *4. Analysis & Results*

3.5.2.3.3 Changes in assets

Fourth, the changes in assets during the first six months succeeding distress is used as a measure to capture to what extent the firm is investing or divesting during early times of distress. The literature seems to include arguments for why both investments and divestments should increase probabilities of turnarounds, as explained in the literature review subchapter *2.6 Variables*.

3.5.2.3.4 Capital expenditures

Fifth, the ratio of yearly capital expenditures to yearly revenue is computed with the aim of capturing the proportion of income that is being spent on capital investments rather than the absolute increase or decrease in capital expenditures.

3.5.2.3.5 Time dummies

Finally, in order to test the effect of time spent in distress on the occurrence of turnaround, we develop a set of time dummies. Twelve dummies are created to each depict whether the given firm has been distressed in one quarter, two quarters, and so on. We would expect that firms which have been distressed in longer periods of time also have relatively lower probabilities of turnaround, ceteris paribus. We believe that time spent in distress is a significant factor when forecasting turnaround and that this has not received enough attention in the empirical models of the extant literature. In *4. Analysis & Results*, we investigate the issue further when developing an optimal turnaround prediction model.

3.5.2.4 Failure Prediction Covariates vs Turnaround Prediction Covariates

Some of the variables described in the previous sections are included in both our failure prediction model and our turnaround prediction model. Due to the conceptual symmetry between our definitions of distress and turnaround, this could be problematic. We argue that this is still acceptable because we are only looking at a subsample of distressed companies when estimating the turnaround prediction model, and the general fundamentals of the companies are therefore different from the total dataset.

3.5.3 Winsorization

A quick glance at summary statistics of all of our variables of interest mentioned in this chapter revealed the presence of absurd outliers. We will not mention all of the reasons for our winsorizations, as it is all fairly generic thinking. However, we will describe a few covariates as examples to give the reader a sense of the relevant considerations. During our data manipulation, we looked at detailed summary statistics for each variable one-by-one and winsorized at the considered appropriate level (between 1% and 5%). Unless stated otherwise, a winsorization of x percent means that we replace the x percent most extreme positive observations by the (1-x)-percentile value of the given variable; and the x percent most extreme negative observations by the x-percentile value of the variable. In some cases, it was only necessary to replace values in one of the tails.

3.5.3.1 Failure data

Summary statistics are divided into two groups of variables: the ones used in the logit-specification which predicts failure; and the ones added to the logit-specification which predicts turnaround. Summary statistics of unwinsorized and winsorized failure prediction model covariates are presented in Appendices A and B. Note that we only display observations where all relevant variables are non-missing. This is because our logit models from *4. Analysis & Results* will automatically restrict the total observations to data where all relevant variables are non-missing.

Many of variables take on unrealistic minimum and/or maximum values (see Appendix A). For instance, a maximum market-to-book ratio of 50517 would mean that investors value the firm fifty thousand times more than the firm is worth on paper (book value). It becomes even more absurd when looking at the minimum value of -46400. Any negative market-to-book ratios do not make much economic sense, since it would mean that either the market value or the book value has a negative sign. Any of the latter would imply that the firm is insolvent. While plausible reasons exist for the occurrence of negative book values (large write-offs in goodwill for instance), MB is meant to capture the relative valuation of the firm in the eyes of investors vs internal accountants. If investors placed zero value on the firm, the numerator in MB would be zero, thus the ratio itself would be null as well. This is the most extreme, plausible case, since investors cannot place a value on the firm that is less than zero. In other words, we place a boundary of zero on the minimum value of MB. When winsorizing the variable at 5% (see Appendix B), it now fluctuates between 0.381 and 8.702 rather than [-46400;50517], which satisfies our perception of the variable as described in this paragraph.

Similar economic reasoning has been used to winsorize other variables at the appropriate level (see Appendix B). The only failure prediction model covariate which we do not winsorize is the stock price per share. However, the price is truncated at 15$ in order to match the assumption set out by Campbell et al. (2008). They argue that such a truncation will allow them to capture the proclivity for distressed firms to trade at low prices per share, without reverse-splitting to artificially bring back a higher stock price. Since distressed firms are expected to trade at lower prices, the aforementioned truncation is expected to enhance the explanatory power of the stock price when forecasting default. That is, we believe that when explaining default, it is more important to determine whether a given firm's stock price is above the selected boundary of 15$ rather than how much above the boundary it is. Campbell et al. (2008) selected this specific boundary of 15$ based on exploratory analyses on their data but without reporting much detail. It is important to note that there is no guarantee that this boundary is necessarily the most appropriate for our data. Nonetheless, for the purpose of replicating the analyses of Campbell et al. (2008), we mirror their choice. Furthermore, PRICE is statistically significant at a one percent level in our modelling later on, which suggests that the truncation boundary is at least somewhat appropriate for our data.

3.5.3.2 Turnaround data

Summary statistics of unwinsorized and winsorized turnaround prediction model covariates are presented in Appendices C and D.

As for the failure model covariates, we will use an illustrative example of our reasoning when winsorizing the turnaround prediction model covariates. STDEBT_ASSETS_Q is the ratio of short-term debt to total assets in quarter q. It captures to what extent a firm is matching its assets with short-term debt as opposed to long-term debt or equity. The idea is that distressed firms are likely to have to take on additional short-term debt in order to survive. This may impede their chances of experiencing a turnaround, since short-term is generally more expensive than long-term debt or equity. Looking at the unwinsorized data, the ratio fluctuates between -0.834 and 1.583. That is, short-term debt constitutes between -83% and 158% of firms' total assets, which makes little economic sense. By construction, STDEBT_ASSETS_Q should not be able to exceed 100%, since assets equal liabilities plus equity, hence at most, the firm can finance its assets fully with short-term debt. In the same spirit, at the very least, the firm can finance its assets with no short-term debt whatsoever. In other words, we impose a logical boundary on the interval of STDEBT_ASSETS_Q as ranging from zero to 1. When winsorizing the variable at 1%, the ratio now fluctuates between 0 and 0.433, in which case we are satisfied.

The particular winsorizations of DEBT_COMP_Q and DELTA_DEBT_COMP_Q deserve a little explanation. DEBT_COMP_Q is a relative measure of the short-term debt to the total debt of the firm. Thus, by nature, unless data have been reported erroneously by some firms, this ratio should need no winsorization. We would expect the debt composition to take on values between 0 and 1. However, the summary statistics (Appendix C) show that the variable takes on values ranging in the interval [-0.505;1]. Thus, we winsorize the data only in the lower end, at a one percent level (Appendix D).

Regarding DELTA_DEBT_COMP_Q, the changes in debt composition in the first six months of distress are symmetrically distributed around 0 with a minimum of -1 and a maximum of 1. These extremities can be interpreted as a 100% change in the debt composition in either direction. While we expect that our predictions of turnaround probabilities would benefit from extreme changes in debt compositions, we already explained our worries with the unwinsorized debt composition data in the previous paragraph. Hence we modestly winsorize DELTA_DEBT_COMP_Q at 1% which yields an interval ranging from -74% to 73%. Overall, we are satisfied with this winsorization since it did not remove all of the extreme changes in debt composition.

3.5.4 Rolling betas

When computing investment alphas in *4. Analysis & Results*, we need an estimate of both the CAPM betas and the Fama French five-factor betas. Note that there are two methods of doing this: static estimations vs rolling window estimation. Without addressing the relative merits of each method, there is a general consensus that beta values estimated using a rolling window is preferred, as the risk of companies changes over time.

We calculate rolling five-factor betas for the companies at the time of investment using a 5-year rolling window. If five years of data are not available, we will instead use 3 years of data. If this is not available, we will use 2 years of data, then 1 year and finally 6 months. If the company has less than 6 months of data, we will not use it in our investment strategy, as we do not consider beta-values calculated from less than 6 months of monthly data to be accurate enough. It should be noted that this methodological choice does not exclude very many observations. Finally, we winsorize the betas on a yearly basis.

3.5.5 Friction-free market

Related to our computation of investment alphas through the use of the CAPM and Fama-French five-factor model, an important assumption follows: there are no market frictions. For instance, this means that there are no transaction costs and that investing in a stock does not affect its price. In the *5. Discussion of the Robustness of the Results*, we illustrate how a combination of aforementioned frictions could potentially explain a portion of the investment alphas.

3.5.6 Unreported variables

Through the process of developing our optimal turnaround prediction model described in *4. Analysis & Results* we experimented with a set of variables which yielded no statistical significance. These variables are briefly mentioned in *4. Analysis & Results*.

3.6 Quantitative method

As a follow-up on our literature review on failure modelling, we dedicate this subchapter to a thorough review of Shumway's (2001) logit specification, which will be used in our following analyses. This logit specification is also used by Campbell et al. (2008).

3.6.1 Addressing selection bias

Commonly, researchers have developed static failure prediction models such as Altman's Z-score or Merton's distance-to-default, while disregarding the many flaws of such static models. Since bankruptcies are relatively rare, researchers commonly gather a sample which spans over many years in order to get enough observations to model from (Chava & Jarrow, 2004). However, static models have an implicit assumption that the set of explanatory variables for each firm is constant through time. Yet we all know that company fundamentals can vary quite significantly from quarter to quarter. Hence, researchers have to arbitrarily pick a point in time where they believe that company fundamentals are solid predictors of failure. For instance, one might select the fundamentals six months before failure as the predictors. This yields a clear selection bias which results in biased and inconsistent estimates of the probabilities of corporate failure. Moreover, by looking only at the fundamentals, say, six months before failure, one would disregard all the information contained in the fundamentals of all the previous months in which the firms were healthy. The static model does not take into account for how long the given firm was healthy before failing.

3.6.2 Shumway's model

Shumway (2001) overcomes the limitations found in static prediction models described above and lays the groundwork for three particular improvements which will be discussed in turn: no selection bias, increase in sample size, and acknowledgement of time-dependent covariates.

To ease the reader's understanding of the following, we make an important clarification. Shumway (2001) develops a dynamic model which is described by two equivalent expressions. Firstly, it can be presented as a hazard model, where the dependent variable would be time spent under healthy conditions (until failure). The firm's probability of failure is then computed in each period based on the firm's most recent financial data. Secondly, such a hazard model is equivalent to a logit model in which each firm-month pair corresponds to an individual observation. The dependent variable is then a dummy which takes on the value 1 if the firm failed in this period and 0 otherwise. In this paper, we choose to proceed with the logit specification due to its relative simplicity in interpretation.

3.6.2.1 Merits of the logit-specification relative to static prediction models

The first main advantage of Shumway's (2001) logit-specification is that it allows for modelling of probabilities of failure at each point in time rather than at the arbitrarily chosen point in time. In essence, the dynamic logit model accounts for each firm-month observation separately rather than ignoring the time element as done in a static model. Secondly, this has an substantial advantage in terms of total number of observations. Our replication of Campbell et al. (2008) required data for the period 1963-2003, i.e. 40 years of monthly data. If we were to use a static model, we would have used the fundamentals as of a specific point in time before failure (i.e. only one observation per covariate would be used to forecast failure). With the logit specification, we are able to use all monthly observations to forecast with instead. Thus, given that the company has existed for all fourty years, we now have 40 x 12 = 480 times more data to use in our forecasts, which results in much more accurate estimates. Thirdly, by explicitly accounting for time, the logit-specification allows us to include time-dependent variables. Since all of the variables for which we collected data varied through the sample, this speaks for the use of a binary logit model to predict corporate failure.

Alternatively, we could have used a probit model to predict probabilities of failure, since the probit function assumes a similar shape to the logistic function. Nonetheless, the calculations and interpretations of the estimates would be more cumbersome. Additionally, Campbell et al. (2008) used a logit specification, hence our replication will as well.

3.6.2.2 Binary logistic model expression

Let Y be the dichotomous response variable. In our case, Y = 1 corresponds to 'failure of the firm' and Y = 0 corresponds to 'non-failure of the firm'. Let X be the vector of covariates $\{X_1, X_2, \dots, X_k\}$

A logistic regression model is then defined as the probability that Y = 1 given the set of covariates ***X***:

$$\text{Prob}(Y = 1|\boldsymbol{X}) = [1 + \exp(-\boldsymbol{X}\beta)]^{-1} = \frac{\exp(\boldsymbol{X}\beta)}{1 + \exp(\boldsymbol{X}\beta)}$$

3.6.2.3 Binary logistic model assumptions

Many key assumptions that are necessary for linear regressions are not required when running a logistic regression. A computational advantage of the logistic specification is that the model is expressed in terms of direct probabilities, i.e. the outcome variable can be interpreted immediately as Prob(Y=1|***X***). The distribution of our outcome variable is entirely defined by the true probability of Y=1. Therefore, we do not need to make any assumptions about the distribution of our outcome variable. By construction, the binary logistic model makes no assumptions about the distributions of the explanatory variables either. In other words, no distributional assumptions are made at all regarding the independent and dependent variables (Harrell, 2015). In addition, the logistic regression does not demand linearity between covariates and the outcome variable, nor does it demand residuals to be normally distributed, nor homoscedasticity (Harrell, 2015). The logit model does, however, rely on a few assumptions which will be discussed in turn:

Assumption 1: The dependent variable is a dummy variable

Assumption 2: There is a linear relationship between the covariates and the log-odds of the dependent dummy variable being equal to one.

Assumption 3: Additivity of effects i.e. observations should be independent of each other

Assumption 4: Little to no collinearity exists among covariates

Assumption 5: The error term is uncorrelated with any of the covariates

The above specifications of the binary logistic model expression satisfy Assumptions 1 and 2 by construction given a relevant vector of covariates. Assumption 3 is equivalent to saying that our observations cannot come from repeated measurements or matched data. In this regard, we need to remind the reader that our financial statement data are strictly equal in months pertaining to the same quarter. Hence, one could argue that our data collection method has violated Assumption 3. However, this would only be true if all of our covariates were built from financial statement data. Yet, as explained previously, we also include other covariates such as stock price and stock volatility for which we had monthly data. Hence, we are indeed left with a unique set of values for any given month if looking at all of the covariates as a whole. Thus, we are not violating Assumption 3. Assumption 4 is defined somewhat arbitrarily in the sense that 'little' collinearity is a subjective matter. This said, according to Harrell (2015, p. 255) *"… in general, collinearity is not a large problem compared with nonlinearity and overfitting"*. The fulfilment of this assumption will be discussed in more detail in *4. Analysis & Results*. Assumption 5 relates to the potential presence of omitted variable bias. It occurs when any relevant predictor of the probability of failure of the firm is excluded from our logistic model, when this predictor is also correlated with any of our covariates. If assumptions 1-2 were to fail, it would yield a misspecification model bias. If any of assumptions 3-5 were to fail it would cause parameter estimates to be biased predictors of corporate failure. In *5. Discussion of the Robustness of the Results*, we address several robustness checks which have a direct relation to the validity of the assumptions listed above.

3.6.2.4 From logistic to logit

The binary logit model is a simple inverse transformation of the binary logistic model:

$$Logit\{Y = 1|\boldsymbol{X}\} = Prob(Y = 1|\boldsymbol{X})^{-1} = \frac{\log\,[\mathrm{P}(\mathrm{Y} = 1|\mathbf{X})]}{\log[1 - \mathrm{P}(\mathrm{Y} = 1|\mathbf{X})]} = \frac{\log[odds(Y = 1\backslash\boldsymbol{X})]}{\log\,[1 - odds(Y = 1\backslash\boldsymbol{X})]} = \boldsymbol{X}\beta$$

The goal of this transformation is to linearly relate the probability of failure and $\boldsymbol{X}\beta$. The model can now be viewed as a linear regression model in the log-odds that Y=1.

3.6.2.5 Interpreting the logit estimates

Each beta can now be interpreted as the change in the log-odds of Y=1 for each unit change in the corresponding covariate. However, it would be handier to interpret the changes in terms of odds rather than log-odds. This can be done by taking the exponential of both sides of the equation above, yielding $\text{odds}\{\mathrm{Y} = 1|\mathbf{X}\} = \exp{(\mathbf{X}\beta)}$.

It immediately follows that, ceteris paribus, an increase of *x* in X_1 entails an increase of $\exp{(\beta_1 * \mathrm{x})}$ in the odds of Y=1. This is equivalent to an increase of $\beta_1 * \mathrm{x}$ in the log-odds of Y=1 (Harrell, 2015).

3.6.2.6 Maximum likelihood estimation

The optimal set of parameter estimates of the logistic regression are computed using a maximization of the likelihood function. Concretely, this function can be viewed as the joint probability of observing the data. In a binary setting, the likelihood function takes the following expression, where Y_i represents the different binary outcomes and n is the number of observations:

$$L = \prod_{i=1}^{n} P^{Y_i}(1-P)^{1-Y_i}$$

In practice, the likelihood function is often log-transformed due to the desirable statistical properties, in which case it is the log-likelihood function which is maximized. For more details regarding the maximum likelihood estimation, see (Harrell, 2015).

3.6.2.7 Test statistics

Arising from the maximum likelihood estimation, different test statistics can be used to test the null hypothesis that the unknown population parameter *P* ('true' probability of corporate failure) is equal to the hypothesized probability P_0. That is, H_0: $P = P_0$. Three similar hypothesis tests emerge: the likelihood ratio test, the likelihood score test, and the Wald test. The mathematical specifications of these tests will be presented in turn, after which we will specify our relative preference.

3.6.2.8 Likelihood ratio test

The likelihood ratio (LR) test statistic is the ratio between the value of the likelihood function at the hypothesized parameters H_0 and the value of the likelihood function at the estimated parameter values found when maximizing the likelihood function:

$$LR = -2\log\left(\frac{L\ at\ H_0}{L\ at\ MLE}\right)$$

LR is asymptotically chi-squared distributed with degrees of freedom corresponding to the number of estimated parameters. As in any other hypothesis test, it therefore follows that a critical value can be collected from the chi-squared distribution. If the test statistic exceeds the critical value, the null hypothesis is rejected.

3.6.2.9 Likelihood score test

The likelihood score test statistic measures "how far from zero the score function is when evaluated at the null hypothesis" (Harrell, 2015, p. 186). A simplification of this test statistic can be written as follows:

$$S = \frac{(s - nP_0)^2}{nP_0(1 - P_0)}$$

The numerator of the above equation highlights that the score test statistic is based on the difference between the observed amount of corporate failures s and the number of corporate failures expected under the null hypothesis nP_0.

3.6.2.10 Wald test

The Wald test statistic W is defined as the difference between the sample probability of corporate failure p0 found when maximizing the likelihood function, and the hypothesized true population probability.

$$W = (p - P_0)^2 / \left[\frac{p(1 - p)}{n}\right]$$

Note that the denominator is simply a rescaling made with regards to the estimated standard deviation of the maximum likelihood estimation. *W* is asymptotically chi-squared distributed with one degree of freedom.

3.6.2.11 Comparing the test statistics

All three tests are based on the same problematic: We need a measure of the statistical significance of the covariates which we include in our logistic regressions. To illustrate the subtle differences between the three test metrics, let us consider the following example. We wish to test whether the inclusion of the variables NIMTAAVG and EXRETAVG can statistically increase our explanatory power of the occurrence of corporate failure significantly. For the purpose of this example, imagine that we already modelled corporate failure using all the remaining covariates for which we gathered data (but simply omitted NIMTAAVG and EXRETAVG).

To conduct a likelihood ratio test, we would then need to estimate two models – one model using only the original set of covariates; and another model using the full set of covariates (NIMTAAVG and

EXRETAVG included) – and compare the fits (log-likelihoods) of the two models. If the difference in fits would be statistically significant, then we would proceed to include NIMTAAVG and EXRETAVG. Contrarily, the likelihood score test and the Wald test only require the estimation of a single model in order to test the joint statistical significance of a (full or sub-) set of variables. The main difference between the two methods is that the score test does not include NIMTAAVG and EXRETAVG in the estimated model. Rather, it uses the slope of the log-likelihood function to estimate the increment in the chi-squared test statistic if one were to add NIMTAAVG and EXRETAVG to the model.

Commonly, when the true parameters are close to the values set out by the null hypotheses, then the three test statistics tend to agree. However, when the true parameters are *not* close to the values set out by the null hypotheses, then the Wald test, in particular, yields erroneously high standard errors (Harrell, 2015). The Wald test also becomes particularly problematic when dealing with a sample in which the binary response variable has a mean that is close to either zero or one. Our collected data indeed suggests a binary response variable close to zero (i.e. the overall sample probability of corporate failure is close to zero). Hence, this speaks for the use of the likelihood ratio test and/or score as robustness metrics in *4. Analysis & Results*. However, we will also compute the Wald test out of interest although we expect it to be biased. We are not too concerned about a biased Wald test because Harrell (2015) states that in general, the likelihood ratio is to be preferred, which seems consistent with our data at this point.

3.6.2.12 Pseudo-R-squared

To quantify the predictive ability of a logit model one cannot compute a generic R-squared measure due to the nature of the maximum likelihood estimation as opposed to an ordinary least squares (OLS) estimation. As a result, many researchers have attempted to develop their own equivalent pseudo measures of explanatory power, yielding countless pseudo R-squared definitions with significant differences (McFadden, 1974; Efron, 1978; Cox & Snell, 1989; Nagelkerke, 1991; McKelvey & Zavoina, 1975; Estrella, 1998; Sapra, 2004; Veall & Zimmermann, 1994). Therefore, it becomes crucial to clarify how one may use such pseudo R-squared values to make inferences. Note here that the software Stata 15 uses McFadden's definition when computing a logit model.

In the case of a generic OLS R-squared value of 0.40, one can simply interpret it as follows: 'variations in the explanatory variables explain 40% of the variations in the dependent variable'. However, the pseudo R-squared *cannot* be interpreted in such a manner, i.e. on a stand-alone basis. Nonetheless, the pseudo R-squared may be used to compare different models that predict the same outcome on the basis of the same data set. This yields two immediate implications regarding our later analyses. Let us go back to the example described when comparing the three test statistics. The first implication is that it is indeed valid to compare the pseudo R-squared of the baseline model and that of the extended model which includes the variables NIMTAAVG and EXRETAVG. This means that we can experiment with the inclusion of additional potential covariates with the aim of maximizing pseudo R-squared. The second implication is that it would be invalid to compare pseudo R-squared of our in-sample model with that of our out-of-sample model, since the two would not be based on the same data set.

Having described the fundamentals of a logit-model, we now put the theory to use with the aim of replicating Campbell et al.'s (2008) default model.

3.7 Chapter summary

In this chapter we defined the concepts of failure, distress and turnaround that will be used in our analyses. We further collected relevant data and justified the necessary manipulations in order to construct our failure prediction model covariates and turnaround prediction model covariates. Finally, we conducted a thorough review of the dynamic logit regression framework which will be employed both when modelling failure predictions and turnaround predictions. We now proceed with presenting our analyses and results.

4. Analysis & Results

In this chapter, we will present the results of our modelling and testing of investment strategies. The results will be analyzed, interpreted and discussed throughout the chapter that will contain four main parts: In Part 1, we replicate Campbell et al.'s (2008) approach to modelling failure. In Part 2, we use the failure probabilities modelled to set up four investment strategies and two robustness checks related to these investment strategies in order to compare results with the findings of *In Search of Distress Risk* (Campbell, Hilscher, & Szilagyi, 2008). In Part 3, having defined stocks with a relatively high probability of failure as being distressed, we produce a model to predict turnarounds from this state of distress. Finally in Part 4, we use the predicted probabilities of turnaround to test, whether one can improve the stock-picking in our superior investment strategy.

After presenting the results and analysis and interpretation of them in this chapter, we will proceed to test the findings out-of-sample in order to comment on their reliability in Chapter 5.

4.1 PART 1: Replicating Campbell et al.'s failure prediction model

The first part of Campbell et al. (2008) which we replicate is their approach to constructing a model that is able to predict corporate failure. Campbell et al. use a dynamic logit model as the one described in *3. Methodology*. First the observations are split into two groups. The first group consists of all the observations where companies experience failure and the second consists of all non-failure observations. The summary statistics of the two groups are depicted in Appendices E and F.

Many of the variables have similar minima and maxima in the two groups, which means that extreme observations of the given variables exist in both groups. This is due to the winsorization of the data, which was explained in *3. Methodology*.

Despite similarities in extremity-values, the specific variables we find necessary to comment on at this time are TLMTA, SIGMA, CASHMTA and MB. The variable total liabilities to total market value of assets (TLMTA) is highest for failure observations. This was expected as an increase in liabilities to assets usually increases the volatility of the equity of a company, which in turn makes it riskier. This is further reflected in the high annualized standard deviation (SIGMA) of failing companies.

Moreover, CASHMTA is higher for failing companies than non-failing companies, however, the two values are very similar. Initially, this might seem surprising as one would think that more cash would decrease the probability of failure, which is often the case. However, the market value of assets acts as the denominator in CASHMTA. Failing companies might divest their assets in order to combat an imminent failure. Moreover, the stock price of a company that is close to failing is usually quite low. These two factors decrease the market value of the assets, which increases CASHMTA. The fact that the values of CASHMTA for non-failing and failing companies are as close as they are, might be an indicator that the fall in market value of assets for a failing company largely offsets the low cash holdings.

The last variable we wish to comment on at this stage is the market-to-book value. This variable is lowest for the failing companies, which is in line with Fama and French's (1996) argument that low market-to-book ratios are usually an indicator of distressed companies.

Campbell et al. (2008) set up their dynamic logit model with a dummy variable representing corporate failure as the dependent variable and the variables listed above as independent variables. They then lag the covariates 12 periods in order to match the dependent variable at time *t*+12 months with the independent variables of time *t*. This allows them to build a model that can be used to forecast failure probabilities in twelve months. We have replicated this approach to our dynamic logit failure prediction model. The results of our model, and the one generated by Campbell et al. (2008) are presented in Appendix G.

The foundations of the two models differ slightly as Campbell et al.'s (2008) model is based on 1,565,634 observations whereas our model is based on 659,846 observations. Furthermore, Campbell et al. have 1,968 (0.126%) failures while we have 389 (0.059%) failures. The reasons for this discrepancy were explained in *3. Methodology.*

As noted above, our model yields a pseudo R^2 of 0.19 compared to a pseudo R^2 of 0.114 in Campbell et al.'s (2008) best model. However, as described in the *3.6 Quantitative Method,* we are not allowed to directly compare the two numbers, since the models were not run on exactly the same data. This said, we have collected our data from the same sources and for the same sample period, hence we can expect a big overlap between our data and those of Campbell et al. While we cannot be certain, it is tempting to conclude that our model better explains the variations in the data.

The pseudo R^2 is not the only thing that differs in the models. First and foremost, our model finds neither NIMTAAVG nor TLMTA to have a significant impact on the likelihood of failure. This finding is in contrast to Campbell et al. (2008)'s p-values for both covariates of less than 0.01. The opposite is true for PRICE, which is found to be significant in our model but not in Campbell et al.'s model. In the rest of this paragraph, the numbers in parenthesis will describe numbers taken from Campbell et al.'s (2008) model.

Other than NIMTAAVG, PRICE and TLMTA, the variables used in the two models are all statistically significant at a 1%-significance level, except for RSIZE, which is significant at a 5%-level in Campbell et al.'s (2008) model. Looking at the signs describing the coefficients, we see that they are alike in the two models for all significant variables.

EXRETAVG has a value of -4.03 (-7.13) meaning that companies which are capable of creating consistent returns above the market are less likely to go bankrupt. The exact interpretation of the coefficient is as follows: If EXRETAVG increases by 1, the log odds increases by -4.03. For instance, say a company has a probability of failure in one year of 20%. This is equal to odds of 0.25[4], which is equal to log(odds) of -1.3863. If EXRETAVG increases by 0.1, log(odds) increases by $0.1 * (-4.03) = -0.403$. This results in log(odds) -1.7893, which in turn is equal to odds of 0.1671. This is equivalent to a probability of failure in one year of 14.32%[5].

Having illustrated the exact interpretation of the parameter estimate for EXRETAVG, our following discussion of the other covariates will focus on the signs of their corresponding coefficients, since these shape our intuition and key findings. The negative sign of the coefficient relating to EXRETAVG is to be expected if one believes that the mechanics of the effective market are working properly. A return above the market should mean that the expectations of the future for a particular company are above the general expectations for the market.

The coefficient found to describe the impact of stock-volatility on failure, proxied by SIGMA, is 1.27 (1.41). We expected this particular coefficient to differ slightly from Campbell et al. (2008) as we have chosen to compute annualized monthly volatilities, whereas Campbell et al. (2008) computed annualized daily volatilities. We also expected a significant coefficient for volatility, since volatility is used in almost all models of stock risk. As owning a stock is equal to owning a part of the underlying business, stock risk is equivalent to the risk of the business and should therefore add to the ability to explain the risk of failure. When stock volatility increases, the required return of investors increases as well due to risk compensation - therefore the coefficient was expected to be positive.

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[4] 0.25 = 20%/(1-20%)

[5] 14.32% = 0.1671/(1+0.1671)

RSIZE is significant at the 1%-level (5%-level). The negative coefficient of -0.47 (-0.045) means that larger companies have smaller probabilities of failure. Reasons for this might be that larger companies usually are more established in their industries than smaller companies. Since larger companies have usually existed for longer periods of time they have therefore had time to move past breaking even while also attaining larger cash holdings (addressed in the next paragraph). On the other hand, larger companies are usually less agile than small companies and are therefore usually worse at reacting to shocks to an industry in which case the coefficient should have been positive.

CASHMTA has a significant coefficient of -1.88 (-2.13). This shows that an increase of cash at hand, relative to the total market value of assets, decreases the likelihood of corporate failure. CASHMTA is in this case used as a proxy for the liquidity of the company. With a high liquidity, the company should be better at reacting to a number of scenarios: Unexpected expenses, such as loss of uninsured equipment, can be dealt with without taking on additional debt if the company wishes to. Furthermore, sudden losses of revenue do not immediately threaten the ability to pay interest expenses on debt. Lastly, a company with a high liquidity is more agile and able to take advantage of new profitable investment opportunities. Liquidity is also a well-researched topic in the extant literature on turnarounds. The turnaround literature points to the fact that when steps are taken to improve liquidity, the likelihood of turnaround increases (Chowdhury & Lang, 1996; Schweizer & Nienhaus, 2017). It seems fair to assume that the factors which help a company experience a turnaround from financial distress are also likely to keep the company out of distress. However, it should be noted that, as explained in the subchapter *2.6 Variables, t*here is no unanimous consent about this effect (Schweizer & Nienhaus, 2017; Gastrogiovanni & Bruton, 2000). Nevertheless, it is reasonable to argue that all these factors combined supports the negative coefficient associated with the covariate CASHMTA.

The market-to-book value, MB, of a company is found to increase the probability of failure as it has a coefficient of 0.09 (0.075). This is counterintuitive when taking the research by Fama and French (1993; 1996) into account. Fama and French (1996) go as far as to define companies that have a low market-to-book ratio as relatively distressed. Additionally, they argue that companies with a low market-to-book ratio persistently have poor earnings and companies with a high market-to-book persistently have high earnings (1993). This is further supported by our summary statistics, depicting the differences between failure observations and non-failure observations (Appendices E and F), which show that when restricting the sample to observations where failure is experienced, the average MB is 1.91 whereas for healthy firms, the average MB is 2.39. This is in contrast to Campbell et al.'s (2008) result, which shows that failing companies have a higher MB than non-failing companies. In short, the summary statistics of the two groups support the argument put forth by Campbell et al., whereas the coefficient in our logit model suggests the opposite. It should be noted that our correlation table (Appendix L) shows that the correlation between MB and TLMTA is of almost fifty percent. This may lead to a spurious relationship between the covariates. On paper, the logit model requires little to no collinearity among covariates. That is, imperfect and/or perfect correlations may have adverse effects on the estimated coefficient. For instance, some of the expected negative impact of a high MB on failure probabilities might be captured by TLMTA. In other words, we suspect MB to be upwardly biased, which could explain the unexpected positive sign of the related coefficient.

The coefficient of PRICE is -0.56 (-0.058), meaning that an increase in stock price lowers the probability of failure. The immediate logical explanation is that when a company fails, the value of its stock will drop to close to zero. Since the value of a stock, in theory, is the probability-weighted present value of all possible future outcomes, a high price should mean that the probability of the price dropping to zero in the future is small. It should be noted that other important factors could affect the stock price without influencing the probability of failure. For instance, if a company that has a stock price of $15 performs a stock split resulting in a lower price per stock, the general economic health of the company has not changed. However, following Campbell et al. (2008), we have winsorized the stock price at $15. Stock splits are often performed to make the stocks seem more affordable to average investors, and it is therefore quite unlikely, that a 2-for-1 stock split would occur when the price is below $30, hence it will not affect our PRICE variable.

The last coefficient is the constant of -20.03 (-9.16). A coefficient of -20.03 can be interpreted as a probability of failure of $\frac{e^{-20.03}}{1+e^{-20.03}} = 0.0000002\%$ when all other variables are set to zero. This interpretation, however, does not bring much practical value, as most of the variables make no sense, if they are set to zero – size being the most obvious example. Nonetheless, it is generally good practice to keep the constant in the regression (Harrell, 2015). Furthermore, the constant is statistically significant at the 1% level.

The discrepancies between our results and those of Campbell et al. (2008) can be due to several other factors, which we will further elaborate on in *6. Limitations.*

4.1.1 Summary - PART 1

Our replication of Campbell et al.'s (2008) failure prediction model has yielded a model with six out of eight strongly significant z-statistics of the covariates. Despite minor discrepancies in the results of the two dynamic logit regression, we validate our hypothesis

H1: Campbell et al.'s approach to predicting corporate failures is replicable

4.2 PART 2: Replicating and testing investment strategies

Having confirmed the replicability of Campbell et al.'s (2008) failure prediction model, we now turn to the conversion of the failure prediction model into an investment strategy. Campbell et al. (2008) argue that an investment alpha can be found by shorting relatively distressed companies and going long in the relatively healthy companies. To test the validity of this finding, we develop seven different investment portfolios throughout this chapter. All the portfolios will be calibrated ultimo January each year. Due to data availability, the investment strategies will all be run from 1973-2004, with the last calibration of the portfolios happening ultimo January 2003 and the end of the investment period will be ultimo January 2004. The effectiveness of all of these portfolios will be measured through (1) the investment alpha according to the Fama and French five-factor model, (2) the investment alpha according to CAPM and (3) the Sharpe ratio of the portfolios.

As a starting point to test the findings of Campbell et al. (2008) that by shorting companies with high probabilities of failure, one can consistently generate positive portfolio alphas, we replicate and test this investment approach using the same investment strategies as Campbell et al. (2008). Campbell et al. (2008) suggest two investment strategies with a positive alpha (investment strategy 1 and investment strategy 2 below).

In the following the employed investment strategies are described:

Investment strategy 1: Invest in the 10% of companies that have the lowest probability of failure. Short the 10% of companies that have the highest probability of failure.

This is the best strategy according to Campbell et al. (2008). This portfolio will be called **LS1090** (long short 90 percentile 10 percentile) from now on.

Investment strategy 2: Invest in the 20% of companies that have the lowest probability of failure. Short the 20% of companies that have the highest probability of failure.

This is the alternative strategy proposed by Campbell et al. (2008). This portfolio will be called **LS2080** from now on.

If the underlying assumption that relatively distressed companies are overvalued holds, then LS1090 and LS2080 would be expected to be profitable, assuming that the long portions of the portfolios are valued correctly. In order to determine such potential profitability, we draw on the portfolio theory set out in the *2. Literature Review* and compute the portfolio alphas using the CAPM and Fama and French's five-factor model. To calculate portfolio alphas, we first need to compute portfolio betas.

4.2.1 Computing portfolio betas: CAPM and the five-factor model

4.2.1.1 Data window for portfolio rolling betas

To be able to establish the alpha values of the investment portfolios we first need to calculate their respective betas values. To reduce the time spent on calculating beta values for the companies[6], we start off by identifying all of the companies that will be included in the investment strategies 1 and 2. As the companies in the portfolio LS1090 is a subsample of the companies in portfolio LS2080, we only need to identify the companies in the latter. For the LS2080 investment strategy, the number of different companies that will be invested in during the 31-year period is 5,034. This means that 5,034 companies (63.8% of the companies in our sample) have been among the healthiest 20% or the least healthy 20% in at least one January of the 31-year period. When looking at the entire period. 23,066 long/shorts will be made.

As explained in *3.5.4 Rolling betas* we calculate rolling beta-values for both the five-factor model and CAPM. The values are preferably based on 5 years' worth of data. However, if five years' of data do not exist at the time of calculation, we use three years' of data, then two, one and finally six months' worth of data.

595 companies have less than 6 months of data and are therefore dropped, reducing the total number of long/shorts made over the 31-year period to 22,471. Of the 22,471 long/shorts we conduct, the amount of data we use to calculate the beta-values is depicted in Appendix H.

[6] With limited computing power, it would have taken us roughly one week to estimate the betas for all firms in the dataset

4.2.1.2 Calculation of CAPM beta:

The CAPM beta is calculated from the three variables *return on the stock, return on the market* and *the risk-free rate.* The definition of these variables for our calculation of the beta values for both CAPM and the five-factor model was described in *3.2 Data Collection.*

The mean of the betas for each year is depicted in Appendix M. Investment_year is the year in which the investment is bought (ultimo January), capm_beta_lower_decile is the mean of the beta value calculated using CAPM for the 10% of companies least likely to fail in the next year, and capm_beta_upper_decile is the mean of the beta value of the 10% of companies most likely to fail in one year. The reason we show the beta values for the deciles instead of the quintiles is that the final choice of investment strategy later in this chapter, makes it more reasonable to focus on the deciles.

Both the upper decile and the lower decile have very low beta-values. This means that, according to our CAPM-regressions, both companies that are relatively distressed and relatively healthy do not vary much with the market. Part of the explanation for the very low beta-values might be found in the R^2-value of our regressions. The average R^2 of all our CAPM-regressions is 0.106. Due to this low explanatory power, we will not comment much further on the beta-values found in the regressions. Instead we will focus on the five-factor model, which is more theoretically sound.

4.2.1.3 Calculation of the betas of Fama and French's five-factor model

As described in *2. Literature Review,* the variables used in the five-factor model are:

- the excess return of the market,
- the return spread of small and large stocks SMB (the size factor),
- the return spread of companies with high and low book-to-market values HML (the value factor),
- the return spread of the most profitable firms and the least profitable firms RMW (the profitability factor),
- the return spread of firms that invested conservatively and firms that invested aggressively CMA (the investment factor).

The factor loadings are presented for each year in Appendices N and O.

The average R^2 for all of our five factor model regressions is 0.36. This is far from ideal as we therefore are unable to explain 64% of the variations in excess returns. However, the five-factor model is recognized in the literature both as a strong theoretical and empirical model for excess returns, which is why we have chosen to evaluate our investment strategies with this model despite imperfect explanatory power. Note that since we short some stocks in our investment strategies, some of the signs of the factor loadings will be reversed from plus to minus and vice versa. For instance, having a portfolio containing only two shorted stocks, equally weighted, with factor loadings on RMW of 0.3 and 0.5 respectively would yield a portfolio factor loading on RMW of -0.4. We will therefore not go too much into detail with the coefficients at this point, but will look at them, when evaluating the investment strategies later. What can be concluded for now is that the relatively more distressed companies seem to load higher on HML and CMA in particular. The higher loading on HML makes sense in that this factor was included in Fama and French's (1996) original three-factor model to capture the higher return of, in their words, "relatively distressed stocks". Note that Fama and French's (1996) definition of relative distress is not the one used in this paper. The high loading on CMA suggests that companies that are headed towards failure are more conservative in their investments. This is not surprising as it is likely that those companies are much more careful with their investments than companies that have a relatively low probability of failure, as their stakes are higher.

4.2.2 Results of investment strategies:

The results of the investment strategies as well as the corresponding alphas and factor loadings of the portfolios are summarized in Appendix P.

4.2.2.1 Investment strategies 1 and 2

Investment strategy 1 and investment strategy 2 are created exactly as in Campbell et al.'s (2008). The idea is that the risky companies have an anomalously low return and negative alphas (Campbell, Hilscher, & Szilagyi, 2008). Shorting these companies should therefore create a positive investment alpha. Our calculations do *not* support these findings. On the contrary, we find a negative alpha using both the five-factor model by Fama and French, and the CAPM-model. For LS1090 the alpha-values over the 31-year investment period average out to -0.153 and -0.263 for the five-factor model and CAPM respectively. These values are -0.09 and -0.17 for LS2080.

As explained in *3.3 Our Replication and Campbell et al. – Main differences*, the only apparent differences between Campbell et al. (2008) and our replication of their paper are (1) the definition of failure (which influences the construction of the concepts of distress and turnaround), (2) the sample size, and (3) the calculation of stock volatility. However, (2) and (3) can be considered relatively small matters compared to (1), and we attribute therefore most of our differences in results to the difference in the definition of failure.

4.2.2.2 Robustness portfolios 1 and 2

Due to the large differences between the results of our investment portfolios 1 and 2 and the portfolios presented in the paper by Campbell et al. (2008), we construct two robustness portfolios C_LS1090 and C_LS2080 to test whether these discrepancies stem from discrepancies in the logit model estimates as elaborated previously. The robustness portfolios are made using the model presented in Campbell et al. (2008) to calculate the probabilities of failure:

Robustness portfolio 1: The first robustness portfolio is similar to LS1090, but with the probability estimated from Campbell et al.'s (2008) failure model. This portfolio will be called **C_LS1090**.

Robustness portfolio 2: The second robustness portfolio is similar to LS2080, but with the probability estimated from Campbell et al.'s (2008) failure model. This portfolio will be called **C_LS2080**.

We recalculate the probabilities of failure, this time using the coefficients estimated by Campbell et al. (2008). We then run the same portfolio constructions using the newly estimated probabilities.

The results presented in Appendix P do not suggest that the discrepancies are due to the differences between our respective models for predicting failure probabilities. Imposing Campbell et al.'s parameter estimates does not change our results significantly. The portfolio C_LS1090 does manage to produce a positive alpha using Fama and French's five factor model, however this alpha is very close to zero. Meanwhile, both portfolios have a negative average return over the period.

In addition to our robustness portfolios and the fact that we check the profitability of the portfolios using two different measures of alpha, we have (unreportedly) chosen to make two additional robustness checks to test the results. We have lagged the investment time by 3 months to make sure that all data were available at the time of investment and we have tried winsorizing the most extreme negative returns each period. None of these tests change the results significantly.

On this basis, we conclude that the effectiveness of the investment portfolios presented by Campbell et al. (2008) is absent in our data.

4.2.2.3 Investment strategies 3 and 4 – Alternative strategies

In order to search for investment strategies that perform better than strategies 1 and 2, and better than the robustness portfolios 1 and 2, we further develop two alternative strategies: strategies 3 and 4. Our idea is here to revert the assumption made in strategies 1 and 2, thus now assuming that relatively distressed companies have far too high risk premiums to offset their actual risk.

Investment strategy 3: Short the 10% of companies with the lowest probability of failure. Invest in the 10% of companies with the highest probability of failure.

This is our first alternative strategy, used to test the assumption that the value of companies that are relatively distressed is too low, and the risk premium is therefore too high. The choice of not only investing in the 10% with the highest probability of failure, but also shorting the 10% of companies, which are most healthy, is in order to mimic the long/short symmetry of strategies 1 and 2. This portfolio will be called **SL1090** from now on.

Investment strategy 4: Short the 20% of companies with the lowest probability of failure. Invest in the 20% of companies with the highest probability of failure.

This is our second alternative strategy, used to test whether a potential underestimation of the values of relatively distressed companies extends into the entire lower quantile. Again, the choice of also shorting the healthy companies is in order to mimic the long/short symmetry of strategies 1 and 2. This portfolio will be called **SL2080** from now on.

We find these alternative investment strategies to be more optimal than investment strategies 1 and 2 and robustness portfolios 1 and 2. Indeed, returning to the results presented in Appendix P, the alternative portfolios (strategies 3 and 4) show positive signs.

First of all, both SL1090 and SL2080 have positive average yearly returns over the 31-year period of 23.12% and 14.6% respectively. Additionally, both investment portfolios produce positive alpha values. In both the five-factor model and in the results produced by the CAPM, SL1090 has the upper hand. It has a five-factor alpha of 0.053 versus 0.020 produced by LS2080. The alpha calculated using the CAPM is significantly higher as SL1090 produces an alpha of .182 in this case, whereas SL2080 produces an alpha of 0.100. The effectiveness of SL1090 compared to SL2080 is further underlined by the Sharpe ratio of SL1090 being 0.126[7] higher than that of SL2080.

Importantly, further examination of SL1090 shows that the majority of the effectiveness of the portfolio comes from the long investment into the relatively risky stocks rather than from the short investment.

[7] 0.614 – 0.488 = 0.126

4.2.2.4 The optimal investment strategy

From these findings we construct a seventh portfolio called L90 which only focuses on going long in distressed stocks.

Optimal investment strategy (L90): Go long in the 10% of companies with the highest probabilities of failure.

In this portfolio, we again divide the stocks into deciles corresponding to their probability of failure in 12 months. We then invest only in the upper decile, the stocks that are most likely to fail. That is, we do not mirror the long investment in the upper decile by a short investment in the lower decile. Everything else is done in the same manner as the earlier portfolios described. The investments occur ultimo January each year. The stocks are then held for a year before the portfolio is restructured. The results of this portfolio are also shown in Appendix P.

L90 has an average return of 64.35%. This produces an extremely high alpha of 0.576 when using CAPM to calculate it. However, it seems that the five-factor model is better at capturing the different types of underlying risk, yielding a humbler alpha of 0.055 over the 31-year period.

This portfolio outperforms the six other portfolios presented in all of our chosen performance measures. It produces the highest alpha both according to the CAPM and the five-factor model presented by Fama and French (1996). In addition, the Sharpe ratio of the portfolio over 31 years is 0.765, compared to 0.488 and 0.614 representing SL2080 and SL1090 respectively. We can therefore conclude that L90 is superior to the six other portfolios and represents our optimal investment strategy.

To explain the high yearly return (64.35%) and the five-factor alpha of only 0.055, we look closer at the factor loadings of the portfolio. L90 has relatively high loadings on SMB and CMA. A 0.53 loading on SMB suggests that a large part of the return can be explained by the additional return on small companies compared to large companies. This is in line with the average market value of the companies that are invested in in L90. Indeed, the average market value of the companies is $15.27 million, compared to an average of $729.79 million, when looking at all available observations in our dataset.

The average loading on CMA through the 31-year investment period is positive at 0.56. As CMA is calculated as the return on companies that have invested conservatively minus that of those that have invested aggressively, it describes the investment premium. The average CMA accumulated over one year from January-December, indicating one year from the time of investment, is 0.24, indicating an average premium of 24 percentage points for companies that invest conservatively. Therefore, according to the regressions used to calculate the five-factor alpha, a large part of the excess return can be attributed to the premium gained from investing in companies that are conservative when it comes to investing. Just like SMB, this is also in line with the fundamentals of the companies the L90 investment strategy picks out. The 1-year growth in assets from the point of investment for the stocks included in the portfolio is $0.64 million compared to $67.15 million, when looking at all available observations in our dataset.

4.2.3 Summary - PART 2

From the analysis above and the results presented in Appendix P, we can conclude the following before we move on. As already mentioned, we cannot confirm the conclusions of Campbell et al. (2008) regarding the profitability of the investment strategies devised in their paper *In Search of Distress Risk* (Campbell, Hilscher, & Szilagyi, 2008). On the contrary, the two proposed investment strategies by Campbell et al. are the ones that perform most poorly out of the seven strategies explored here. Instead, we have found that investing in stocks that are relatively distressed yields a positive excess return. The high return of L90 cannot be explained fully by neither the CAPM model nor the five-factor model. However, the five-factor model can explain the largest part of the excess return: A relatively large part can be explained by the outperformance of small companies compared to big companies and the outperformance of companies that have a conservative investment profile compared to those which exhibit an aggressive investment profile. However, even when taking this into account, there is still an excess return of roughly 5%, that cannot be explained. This suggests that the companies that are relatively distressed compared to the rest of the market are in general undervalued, and an abnormal return can be gained from investing in them. Against these results, we reject our second hypothesis (which was based on the conclusions of Campbell et al. (2008):

H2: Shorting companies with high probabilities of failure yields abnormal returns.

4.3 PART 3: Turnaround prediction model

Having developed a failure prediction model and extracted an optimal investment strategy based on the predicted probabilities of failure, we now turn to answer the second part of our research question: Can the return of our optimal investment strategy be further improved by adjusting the strategy according to predicted turnaround probabilities?

In this chapter we will continue the analysis examining two things: First, can a model, which accurately predicts turnaround be constructed from the data in our dataset? Second, if such a model can be constructed, can it be used in collaboration with the investment strategy L90 to improve this strategy in any way? As a follow-up, in *5.1 Out-of-Sample,* we investigate how the final investment strategy fares out-of-sample, and what the possible reasons are for our results.

4.3.1 Developing a turnaround prediction model

The first step in developing a turnaround prediction model is to define corporate distress and from that define corporate turnaround. This was done in *3. Methodology.* In this chapter, we move on to generating a model based on these definitions.

4.3.1.1 Defining the model

The turnaround prediction model will be defined as a dynamic logit model. Since we are interested in improving the investment strategy which focuses on distressed stocks, we are interested in predicting whether a distressed company manages to turn around within the next year. Therefore, the dependent variable in our model will be 'Turnaround_within_1_year'. This variable is a dummy variable that is 1 if a turnaround happens within the next twelve months and 0 otherwise. Therefore, unless the turnaround happens within the first 12 months of observations for a specific company, the variable Turnaround_within_1_year will always have twelve 1-observations in a row.

To find the relevant independent variables, we start off with a set of variables inspired by the findings of previous research (see *2.6 Variables*), and from there we narrow down the ones that actually have an impact on our model.

To represent the effect of staff layoff, we construct the variables 'delta_emp_00-12' and 'delta_emp_12-24'. These represent the changes in the total number of employees within the first year in distress and the changes in employees within the second year of distress.

To represent investing and divesting, we use the change in assets in the first two years split into four variables covering six months each, 'delta_assets_00_06', …, 'delta_assets_18_24'.

To represent the capital structure of the companies, we use a number of different variables: Total debt to assets, short term debt to assets and long-term debt to assets. On top of this, we also incorporate these into deltas in the same way as was done with (changes in) assets. We are aware that there is a large overlap in the definitions of debt and liabilities, as debt is a subgroup of liability. We are alert to this when constructing the model.

On top of testing the effect of the capital structure, we also test the effect of the debt composition. To do this, we construct the variable 'debt_comp', which is short term debt to total debt. The changes in debt composition is captured by four variables of ‘delta_debt_comp_xx_xx’, constructed in the same way as the delta-variables for assets.

Capital expenditures are represented by ‘capx_revenue’, which measures how big a part of the revenue goes towards CAPEX. Again, this is also constructed as deltas, however only on a yearly basis, meaning changes within the first year in distress and changes within the second year.

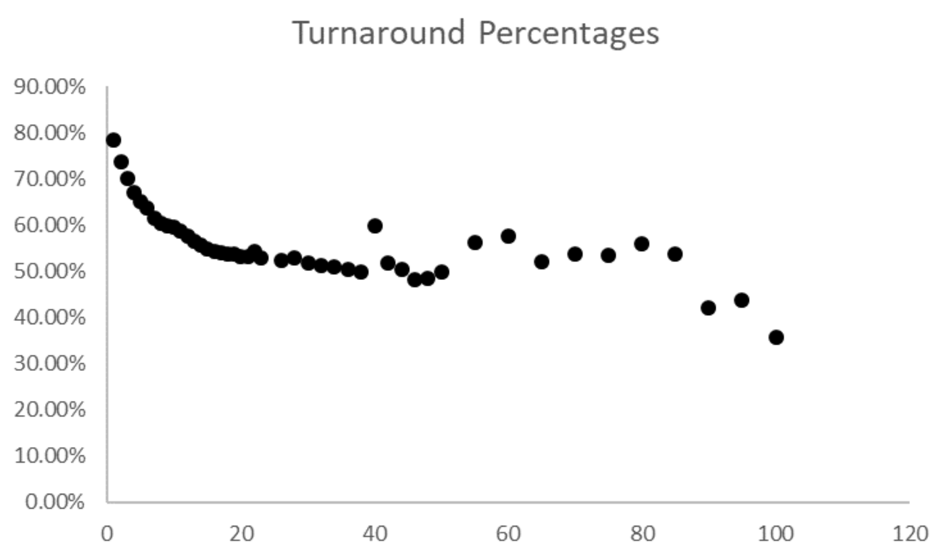
The last variable that both represent a “static” number and changes in that variable is the current ratio, which is used to measure the liquidity of the company. The changes are again represented by four delta variables with a 6-months span each.

As can be noticed, changes in employees and changes in the CAPEX to revenue ratio are the only ones that are measured on a twelve-monthly basis instead of six months. This is due to the limited availability of quarterly data compared to yearly data. The reason we construct these deltas, and the reason we construct more than one, is to capture the effect of the timing of these changes. The timing of changes has been highlighted in much of the previous research on the subject (cf. *2.5 Corporate turnaround* and *2.6 Variables*) and is thought to be one of the main reasons why different papers find contradicting results on the impact of certain variables on the probability of turnaround.

On top of the variables above, which are all well researched variables, we add one that is often missing in the literature – namely, time spent in distress. It is not highlighted as a main variable by Schweizer and Nienhaus (2017) and does not appear in any of the papers referenced in *2. Literature Review.* Nevertheless, there are indications that companies that have recently entered into distress are more likely to experience a turnaround than companies that have been in distress for a longer period of time. To take this time parameter into account, we construct twelve dummy variables, each representing how many quarters the company has been in distress up until two years. These variables are called d_distress_time_10_”x”q, where “x” can take the values from 1 to 12. In the final model, only “x” from 1 to 8 have been included for this variable. This means that the baseline for d_distress_time_10_”x”q is companies that have been distressed for more than 2 years (i.e. 8 quarters). That is, if all the d_distress_time_10_”x”q variables are equal to zero, the model describes a company that has been distressed for more than 8 quarters.

If we look at all companies that go into distress at some point in our dataset, we see that 78.49% of those companies manage to leave the riskiest decile and perform a turnaround. If we only look at the companies that have been in distress for 6 month or more, the percentage drops to 65%. This trend continues, as depicted in Figure 5.

Figure 5 – Turnarounds over time spent in distress



Note: This graph shows the effect of time spent in distress on the percentage of sampled firms that experience a turnaround at some point in the future (within the sample period). The sample period runs from 1963 to 2004, and the graph includes all distressed firms in our dataset. The Y-axis shows the percentage of distressed companies that manage to perform a turnaround at some point in the future. The X-axis shows the subset of the sample that we are looking at as a function of time. For instance, if the X-axis is 20, we are looking only at companies that have a total time spent in distress of 20 months or more.

Source: Own computation based on data from COMPUSTAT (2019) and the Center for Research in Security Prices (2019).

As can be seen in the graph, the percentage of companies that manage to turn around drops significantly in the part of the X-axis where we narrow the sub sample we are looking at from all companies that have a total time spent in distress above 0 months to all companies that have a total time in distress above 30 months. From around 30, it starts to stagnate until it drops again around 90. We chose to ignore the drop after 90, as the number of companies in the subsample has dropped to less than 20 at this point. This graph clearly signals that time spent in distress could be a significant factor when calculating the probability of turnaround.

4.3.1.2 Final Turnaround prediction model

Using the previously described variables and the practice of trial and error, we find our optimal turnaround prediction model (see Appendix Q).

As can be seen, a lot of the variables presented initially are not included in the final model. They have been removed either due to insignificance, worsening of the explanatory power of the model or a lack of observations. Note that we will not specifically interpret the size of the parameter estimates in terms of log(odds), odds, or probabilities, since such interpretation has been illustrated with the example of EXRETAVG in our failure prediction model. Instead we focus on the covariates' signs and correlations. We start by highlighting a few correlations.

From the correlation matrix (Appendix R), it can be seen that short-term debt to assets and debt composition have the largest correlation of 0.5472. This comes as no surprise, as an increase in short-term debt will increase both values. Short-term debt to assets also has a high correlation of 0.3602 with total liabilities to assets (TLMTA), which can be explained by the fact that short-term debt is a part of the total liabilities as well as the denominator in the two ratios being equal. Additionally, market-to-book has a correlation of -0.4857 to TLMTA. An increase in the market value of assets will lead to an increase in market-to-book and a decrease in TLMTA, as it constitutes the denominator in the ratio.

In general, none of the signs of the correlations seem alarming, however we need to address the impact of their magnitudes regarding potential multicollinearity. Relating to Assumption 4 of the logit model as expressed in *3.6.2.3 Binary logistic model assumptions*, we require little to no collinearity among covariates. Since, this textbook definition is vague in nature, the fulfillment of this assumption remains subjective. That said, most of the presented correlations are below forty percent, which is, all things considered, not alarming. Especially, since we can characterize the biases (as downward or upward) as illustrated with the correlations between short-term debt to assets and debt composition, for instance. However, we would have preferred no correlation whatsoever among covariates. Therefore, the potential biases in our parameter estimates are duly noted, but we proceed with our optimal turnaround prediction model aware of its limitations.

4.3.1.2.1 Liabilities and debt composition

To describe the effects of liabilities and debt composition, our final model uses three different variables. Total debt to total assets (TLMTA), short term debt to total assets (stdebt_assets_q) and debt composition measured as short term debt to total debt and change in debt composition during the first year of distress (delta_debt_comp_q). Both TLMTA and stdebt_assets_q are significant at a significance-level of less than 1%. Debt_comp_q is significant at a 10% significance level, whereas delta_debt_comp_q is not significant. However, if delta_debt_comp_q is removed from the model, it causes insignificance in other variables. This might highlight the interplay between several of our included covariates and potential omitted variables. The issue of omitted variable bias will be further addressed in *6. Limitations.* TLMTA has a coefficient of -0.4199 and stdebt_assets_q has a coefficient of -1.1114. This indicates that increases in liabilities, especially the subgroup of liabilities, short-term debt, has a negative effect on the probability of performing a turnaround within a year. The relationship that the absolute value of the coefficient on short-term debt to assets is higher than that of total liabilities to assets, is further underlined by the negative coefficient on debt composition. Debt_comp_q has a coefficient of -0.1364, meaning that an increase in short term debt relative to total debt decreases the probability of turnaround. This is further underlined by the negative coefficient of delta_debt_comp_q, which indicates that a decrease in the short-term debt to total debt ratio occurring within the first year of distress should affect the probability of turnaround positively. However, this coefficient was, as already noted, insignificant.

The relationships between reducing the amount of liabilities to assets and the probability of turnaround is supported by the existing literature (Giroud, Mueller, Stomper, & Westerkamp; Zingales, 1998; Schweizer & Nienhaus, 2017) . However, our model adds the notion that the reduction in liabilities should mainly be focused on the short-term debt to assets ratio. The literature argues that the change in the ratio should come from reducing the debt-part of the ratio instead of increasing the assets (Giroud, Mueller, Stomper, & Westerkamp, 2012).

4.3.1.2.2 Investment and divestment

To look at the effect of investments and divestments on the probability of turnaround, we use the change in assets described via the above explained variables 'delta_assets_xx_xx'. Even though we initially used four different delta variables, we only found the one that describes the change in assets in the first six months after entering distress to be significant. As can be seen from the overview of the model (Appendix Q), the coefficient is positive at 0.4616 and is significant at a significance level lower than 1%. This indicates that early investments in new assets have a positive impact on the likelihood of experiencing a turnaround. This finding suggests, in relation to the implications of the other coefficients, that investments should not be funded using short-term debt. As described in *2. Literature review*, the effect of investing or divesting a company's assets during distress is a topic the literature does not have a clear answer for. However, Schweizer and Nienhaus (2017) point to the fact that this incertitude is most likely due to the difficulty in tracking whether the investments made are good or bad investments. Simply increasing assets should not in itself be enough to improve the probability, but smart investments should be. Under the assumption that the companies in our dataset on average perform smart investments when they increase their assets, we can add to the literature mentioned in *2. Literature Review,* that the effect of these investments is significant, when they are performed early in the distress-period. It should be noted that an increase in assets does reduce both TLMTA and stdebt_assets_q, both of which have negative coefficients, and therefore further increases the probability of turnaround. Due to this effect, and to the correlations highlighted previously in Appendix R, it is most likely that these variables share some explanatory power.

4.3.1.2.3 Liquidity indicators

The liquidity indicators used in the model are CASHMTA and W_current_ratio_q. In addition, we also have W_delta_current_ratio_00_06, representing the change in current ratio in the first six months of distress These variables are important to look at together, because they show contradicting results. W_current_ratio_q has a coefficient of -0.0537 and CASHMTA has a coefficient of 1.76. What this means is that increases in current ratio decreases the probability of turnaround, while increases in cash increases the probability. Both coefficients have p-values of 0.000. At first glance, it is noticeable that the the absolute value of the coefficient of CASHMTA is quite higher than that of W_current_ratio_q, but this effect is close to levelled out by the difference in CASHMTA and W_current_ratio_q. Distressed companies have an average CASHMTA of 0.09 and a current ratio of 2.48. If we time both coefficients with the value of the respective variables, we find a value for the coefficient of CASHMTA and the average of the variable of 0.1575. The same calculation for W_current_ratio_q yields a value of -0.134. The net value is therefore positive, but close to zero. Removing either value from the model still yields the same signs for each coefficient. Short term debt is a part of the denominator in the current ratio, however, removing St_debt_assets_q still does not change the result significantly. The variable W_delta_current_ratio_q_00_06 also has a negative coefficient, indicating that increases in current ratio early in the first six months of distress reduces the probability of turnaround. However, the coefficient is only significant at a 10% significance-level. We are not able to give a reasonable suggestion as to why an increase in current ratio should decrease the probability of turnaround. However, some of the explanation may come from the fact that current assets are an integral part of total assets which in turn are a part of a large number of the variables used, and often act as the denominator in the ratio-variables.

The conclusions that can be drawn from the coefficient is that, according to our turnaround prediction model, decreases in the current ratio seem to increase the probability of turnaround. However, coefficients of other variables suggest that this decrease should not come from decreasing cash nor from increasing short-term debt. Increasing cash in itself has a positive impact of turnaround. A reason for this could be that increased cash holdings leads to more agile companies that are able to take advantage of sudden and time-limited investment opportunities and are resistant to sudden shocks to an industry. This is also supported by the literature on corporate turnaround (Zingales, 1998).

4.3.1.2.4 Time in distress

As mentioned previously, our final turnaround prediction model includes dummy variables describing how many quarters the company has been in distress. All the coefficients are positive and all but the two describing the seventh quarter and eighth quarter are significant at a significance level of less than 1%. The general trend in the coefficients is that they become lower and lower, the longer a company has been in distress. It indicates that companies are more likely to perform turnaround, when they have only been distressed for a short period of time. The coefficient for d_distress_time_10_7q is still significant at a 5%-level, while the coefficient for d_distress_time_10_8q is not significant. This is not surprising, when looking at Figure 5. As mentioned earlier, the graph stagnates after the first two to three years. The alternative for one of the dummy variables to be equal to 1 is for all of them to be zero, indicating that it is a company that has been distressed for more than eight quarters. Since the graph stagnates at this point, it was expected for the coefficients for the dummy variables to be less and less significant.

4.3.1.2.5 Price and market value

PRICE has a positive coefficient of 0.8546 and a p-value of 0.000. This means, that a higher price on a company's stocks (winsorized at the upper level of $15) has a positive impact on the probability of turnaround. A positive coefficient for PRICE is not unexpected, since it is one of variables used in predicting failure, and therefore one of the variables defining whether the company is in distress or not. As it had a negative value in the failure prediction model, a positive value is expected now.

The same is true for RSIZE and MB. Both of which also have coefficients that have the opposite sign from what they had in the failure prediction model. The fact that the coefficient for MB is negative at -0.1233 is surprising. Following the same reasoning as for the failure prediction model, this is not in line with the research of Fama and French (1996) nor with the summary statistics in Appendices E and F.

As described previously, the fact that our model uses some of the same variables as the model, which describes whether they are in distress or not could be problematic. To test that all of our explanatory power does not come from the variables we have included from the initial model, we run the turnaround prediction model again, but without some of these variables. This robustness test does not seem to suggest that all of the explanatory power comes from these variables. Examples of these tests are as follows. Removing TLMTA reduces pseudo R^2 to 0.1375 and increases the p-value for a few the covariates.

Removing CASHMTA reduces the pseudo R^2 to 0.1331. And finally, removing RSIZE reduces the pseudo R^2 to 0.1188. If all the variables from the initial model are removed from this model, it reduces the pseudo R^2 to 0.0644. It can therefore be concluded that these variables do add explanatory power to the model, however, the model does not become obsolete by removing these variables.

4.4 PART 4: Turnaround-adjusted investment strategy

As formerly mentioned, the optimal investment strategy that was found in this paper was L90. This investment strategy consisted of investing in the 10% of stocks most likely to fail in one year from the moment of investment. Having developed a theoretically sound turnaround model, we now seek to improve the results of this strategy by using the turnaround prediction model to predict the probability of turnaround for each stock in each period of time. These probabilities are then used ultimo January each year, when the portfolio is being calibrated. The idea is that we initially find the 10% of stocks that are relatively distressed and from this subsample, we chose and invest only in the companies that are most likely to perform a turnaround. The effectiveness of this addition to the investment strategy is measured in changes in the five-factor alpha and changes in the Sharpe ratio.

Preferably, we would want to compare the investment strategy and its improvement over the same period, namely 1973-2004. However, to make sure that the potential improvement of the investment strategy comes from the turnaround prediction model, we will have to manipulate the original investment strategy first. The turnaround prediction model uses a number of variables that were not included in the failure prediction model, e.g. current ratio and debt composition. The source we use for this kind of data is COMPUSTAT, which does not have data on the variables available for all companies. When looking at current ratio as an example, short-term assets and short-term liabilities are only available for a very low number of companies in 1973. As time progresses in the dataset, it becomes available for more and more companies, which is why this will not be an issue in *5.1 Out-of-Sample*, when we test the strategy out-of-sample for the period 2007-2018. However, a lack of data availability such as the one just described limits the number of companies we can invest in in our investment strategy (in-sample) that includes the turnaround prediction model, since we can only invest in companies where we can actually calculate the probability of turnaround. To make sure that the potential improvement comes from the model and not from the limits applied to potential investments due to lack of data, we create a new portfolio as our baseline portfolio. This portfolio follows the original idea of the L90 portfolio but limits the choice of stocks to those that have all variables available that are used in our turnaround prediction model. Since these variables are only available for a very low number of companies at the start of the data period, we will have to limit the investment period as well. To make sure we have a sufficiently large dataset to construct the portfolio from, we chose a new investment period from 1994-2004.

The addition to the strategy is the choice of only investing in the companies with the highest probability of turnaround. The cut-off point for when a company is part of the subset with "highest probability" is determined through a process of trial and error. In Appendix S, we have reported the results from having the following four cut-off points. Top 90%, top 75%, top 50%, top 25%. We would have liked to test also top 10% and top 5%, however, the dataset is not large enough to gain a good understanding of the effect these strategies would have. As we are going to test this investment strategy out-of-sample on an investment period from 2007-2018, which has more data on the variables used to calculate the probability of turnaround, we will test top 10% and top 5% at this point.

The strategies we test are named as follows:

- The benchmark portfolio, which is based on the L90-strategy but is limited as described above is called **L90Bench**.
- For each of the turnaround-adjusted investment strategies, the names will be **L90Top90, L90Top75, L90Top50, L90Top25** respectively

The results of the investments strategies are summarized in Appendix S. It is immediately notable that the benchmark portfolio produces better results than the original L90. This can be contributed only to the limits we have put on the dataset for this comparison. Since COMPUSTAT did not at the time collect variables on all data for all companies, the data might be biased towards companies that outperformed the most, since these have been of the greatest interest to the users of COMPUSTAT. In addition, we also changed the time frame of the entire investment strategy to 1994-2004 (First stock purchase occurring in January 1994 and last purchase in January 2003). For now, we ignore the improvement to the restrictions on the dataset and accept L90Bench as the benchmark to which we can compare the turnaround adjustments to the model. All the adjusted portfolios underperform the benchmark when it comes to the five-factor-alpha. The benchmark portfolio produces an alpha of 0.2726, and the portfolio that comes closest to this alpha is L90Top90, which produces an alpha of 0.1961. Even though the alpha is lower, the Sharpe ratio of L90Top90 is quite a bit higher than that of L90Bench, beating it by 0.2041.

All other turnaround-adjusted portfolios underperform, when it comes to both the alpha and the Sharpe ratio compared to L90Bench. When looking at the factor loadings, the absolute values of loadings, except for RMW, increase as we narrow our portfolio to fewer companies with higher probabilities of turnaround. There is a possibility that this is due to market mechanisms, however, it can also be a consequence of the substantial reduction of our sample size. In some years, for the investment portfolio that only looks at the 25% of distressed stocks that have the highest probability of turnaround (**L90Top25)**, we only have three stocks in our portfolio. We therefore argue that with a larger sample set, the increases in the number of stocks will diversify some of the risk and therefore produce better results. As mentioned already, this is not possible in-sample, due to the lack of available variables on a large portion of the companies. However, in the next chapter, we shall look at a more recent dataset, which allows us to overcome this problem, while also testing the investment strategies both with and without the turnaround-adjustment out of sample.

4.4.1 Summary - PARTS 3 & 4

Though having developed a theoretically sound turnaround prediction model, our results in Appendix S point to the fact that being able to predict turnaround probabilities does not translate into an improvement in the investment strategy. The only improvement that seems to be gained is that of improving the Sharpe ratio, when cutting out the 10% of stocks that are least likely to turnaround within a year. Nevertheless, this improvement of the Sharpe ratio comes at the cost of a lowering of the investment alpha. Against these results, we reject our third hypothesis set forth in *1.4 Hypotheses*:

H3: By developing and applying a theoretically sound and empirically accurate model for corporate turnarounds, the performance of the investment strategy that is based on failure probabilities can be further enhanced.

Having only defended the theoretical groundings of our turnaround prediction model, its empirical accuracy will be defended in the following chapter (see *5.1.2 The ability of our model to predict turnaround out-of-sample*) along with additional robustness checks.

5. Discussion of the Robustness of the Results

In this section, we turn to address the robustness of our findings, using a number of different robustness tests.

5.1 Out-of-sample

As a robustness test to our key findings, we first attempt to replicate and test them out of sample. As described in *3. Methodology*, our out-of-sample dataset spans from 2007 to 2018 and is collected from the COMPUSTAT and CRSP databases. A detailed walk-through of the data manipulation has been presented in *3. Methodology.*

Specifically, we test the following findings out-of-sample:

- (1) The investment strategy L90 outperforms the market. We found the optimal investment strategy in the first part of our analysis to be L90. The findings pointed to relatively distressed stocks having a risk premium that was too high and that a positive investment alpha could be found by investing in these stocks.

  We expect that the investment strategy will have a positive investment alpha and indicate a general undervaluation of relatively distressed stocks.

- (2) The developed turnaround-model accurately predicts actual turnarounds out-of-sample. Distress and turnaround are defined in the same way out-of-sample as they were in-sample. We test, using the coefficients derived from the model in *4.4.1.2 Final Turnaround prediction model*, the correlation between predicted and actual turnarounds.

  We expect that the turnaround-model will provide probabilities of turnaround out-of-sample that will be positively correlated with actual turnarounds.

- (3) The turnaround adjustment to L90 improves the portfolio performance. Our in-sample tests of a turnaround-adjusted investment strategy were inconclusive due to the sample size ending up being too small. We wish to test whether a large number of observations out of sample will produce similar results to those found when using a suboptimal low number of observations in-sample.

Due to the results in sample, we expect that when investing in the 10% most distressed stocks, the generated portfolio return can be improved by strategically excluding stocks pertaining to firms with low probabilities of turnaround. Discarding the 10% of distressed stocks with the lowest probability of turnaround each year (that is, investing in the 90% of stocks most likely to perform a turnaround) will improve the Sharpe ratio of the investment portfolio, but will diminish the investment alpha.

5.1.1 Robustness of the investment strategy L90

The optimal investment portfolio L90 is constructed in the same manner as in-sample. The results of L90 out of sample are displayed in Appendix T.

To test the first finding, we first calculate the probability of failure in exactly one year for each period in time. This is done using the coefficients of the dynamic logit model developed in *4. Analysis & Results*.

As we found alpha using the CAPM to be a poor estimate of the performance of the portfolio in-sample, we only measure the alpha using the five-factor model when we look at the performance of the investment strategy out-of-sample. The calculation of this five-factor alpha is conducted in the same way as it was in sample. The factor loadings for each company are calculated using a rolling regression, as previously.

The investment strategy is run twice. Once including the financial crisis of 2008 and once excluding the crisis. Hence, the two investment periods will be 2007-2018 (L90_OOS_07_18) and 2011-2018 (L90_OOS_11_18).

The investment strategy performs extremely well both when including the financial crisis and when excluding it. When including the crisis, the portfolio L90_OOS_07_18 produces a return of 0.5541 whereas excluding the crisis L90_OOS_11_18 yields a return of 0.6194. These numbers are very similar to the numbers produced in-sample by L90, which yielded a return of 0.6435. The same goes for the standard deviations, which are 0.722, 0.6705 and 0.772 for the three portfolios respectively. These similar returns and standard deviations, in turn, produce almost similar Sharpe ratios. Though it must be noted that due to a slightly lower standard deviation and a slightly higher excess return for L90_OOS_11_18, the Sharpe ratio of this portfolio is approximately 0.17 higher than those of the other two portfolios. However, this is where the similarities between in-sample and out-of-sample results come to an end. Even though the return and standard deviation seem alike, the investment alpha found using the five-factor model is far more extreme out-of-sample. In-sample L90 presents an investment alpha of 0.0553, whereas, out-of-sample, L90_OOS_07_18 and L90_OOS_11_18 have alphas of 0.4396 and 0.563, respectively. To better understand these alphas, we look at the factor loadings of the portfolios.

Two factor loadings that were of most interest in the initial investment strategy L90 -SMB and CMA - have shifted to negative numbers in the out-of-sample results. The same goes for RMW. The factor loading concerning the excess return of the market has remained largely unchanged, while HML has dropped to about 0. We will comment further on the factors and the factor loadings later in *5.1.3 The turnaround-adjusted investment strategy*.

If we combine the finding of an extremely high alpha gained from the investment strategies out of sample and the fact that our in-sample investment strategy produced an alpha of 0.0553, two explanations present themselves. The first explanation would be, that these relatively distressed stocks in general are undervalued and that the average investor looks at distress compared to the general market rather than looking at distress as a product of unhealthy financials. What we mean by this is, that when looking at all the companies invested in in-sample, the average probability of failing in one year from the moment of investment is just 0.63% with a standard deviation of 0.93%. Moreover, out-of-sample, the average probability of failing is 0.36% with a standard deviation of 0.46%-points. Even though these companies are the 10% riskiest companies at the time of investment, their probabilities of failure are still very low, and therefore the risk premium gained from investing in them should arguably not be as high as our data suggest. Thus, one explanation could be that investors view risk as a relative measure and always compare the riskiness of one company to the riskiness of other companies instead of viewing risk as an absolute value that is independent of other companies' risk-profiles.

The second explanation for the high alphas could be that our computation of investment alphas is flawed. This is underlined by the low average explanatory power of our implemented five-factor models on the L90-strategies. Indeed, when looking at the distressed companies, the R-squared is found to be equal to 41.09% in-sample and 23.99% out-of-sample. In other words, we do not successfully replicate the large R-squared values of around 90% found by Fama and French (2015) themselves; or put differently, an extra risk factor that captures the distress premium could advantageously be added to the Fama and French five-factor model. As mentioned previously, HML is meant to capture such distress premium yet it does not – at least not in our sample with our definition of distress. Therefore, we argue for the explicit derivation of a sixth factor RMS in *8.4 Distress factor* later in this paper.

Altogether, the results of the out-of-sample robustness test support our findings from the in-sample analysis confirming that a positive investment alpha can be generated by going long in the distressed stocks, and that this positive alpha indicates an undervaluation of relatively distressed stocks.

5.1.2 The ability of our model to predict turnaround out-of-sample

Our second objective is to test the robustness of our turnaround prediction model out-of-sample. The coefficients of the turnaround prediction model developed in *4. Analysis & Results*, are used in our out-of-sample dataset to calculate the probabilities of turnaround within one year. The distribution of the probabilities computed using the turnaround prediction model are summarized in Figure 6.

Figure 6 – Summary statistics of the predicted probabilities of turnaround within one year

pr_turnaround

	Percentiles	Smallest		
1%	.0243767	.0027361		
5%	.0592105	.0027739		
10%	.0905793	.0044106	Obs	31,208
25%	.176902	.0049035	Sum of Wgt.	31,208
50%	.3356661		Mean	.3605838
		Largest	Std. Dev.	.2159927
75%	.5269847	.9931418		
90%	.6685596	.9964262	Variance	.0466528
95%	.7420418	.9967381	Skewness	.3818176
99%	.8529036	.9973288	Kurtosis	2.208145

Note: This figure presents detailed summary statistics of the predicted probabilities of turnaround within one year. These probabilities stem from our dynamic logit turnaround prediction model. The sample period runs from 2007 to 2018.

Source: Own computation based on data from COMPUSTAT (2019) and the Center for Research in Security Prices (2019).

As can be seen, the average probability of leaving distress within a year for all companies in distress is 36.06%. Moreover, the amount of observations suggests that we are able to calculate the probability of turnaround for a larger number of the companies than we were in-sample, even though we focus on a significantly lower number of years out-of-sample than we did in-sample. In-sample, we had only 13,112 observations of companies that experience a turnaround, whereas out-of-sample we have 31,208 observations.

To test the effectiveness of the turnaround prediction model out-of-sample, we construct three variables. The first variable is d_turnaround_within_1_year. As in the in-sample analysis, this variable serves as the dependent variable of our prediction model and takes on the value one if a turnaround occurs within the next twelve months (and 0 otherwise). This is the variable we want our model to be able to predict. The second variable we create is a random variable that has a uniform distribution called randuni. The third variable is a random variable that is normally distributed called randnorm. To test the assumption that the probabilities computed using the prediction model accurately forecast actual turnaround outcomes out-of-sample, we investigate the specification of predicted outcomes relative to the actual ones. This is done by looking at the correlation between the variable describing the probability (pr_turnaround) and turnaround_within_1_year which should be positive and of high order of magnitude when limiting the observation set to companies in distress. In the same correlation matrix, we also include the two random variables to test whether our predictions simply correlate with actual outcomes due to chance. That is, whether our predictions are more accurate than those of two random variables with different underlying distributions. The results are presented in Figure 7.

The correlation between the probability of turnaround within a year and the actual occurrences of the event is of 0.551. The correlations between the two random variables, randuni and randnorm, and d_turnaround_within_1_year are of -0.0046 and 0.0126 respectively.

Figure 7 – Correlation matrix: Testing turnaround prediction accuracy

Variables	(1)	(2)	(3)	(4)
(1) pr_turnaround	1.0000			
(2) d_turnaround_1~a	0.5510	1.0000		
(3) randuni	-0.0025	-0.0046	1.0000	
(4) randnorm	0.0036	0.0126	0.0013	1.0000

Note: This figure is a matrix of correlations that has the purpose of supporting the accuracy of our turnaround predictions. The variables are the predicted probabilities of turnaround within one year stemming from our dynamic logit turnaround prediction model (pr_turnaround); a dummy variable that takes on the value 1 if the given sampled firm actually experienced a turnaround within one year (d_turnaround_within_1_year); a generated random variable that follows a uniform distribution (randuni); and a generated random variable that follows a normal distribution (randnorm).

Source: Own computation based on data from COMPUSTAT (2019), the Center for Research in Security Prices (2019) & own simulation of random variables.

We thereby confirm the superior forecasting power of our variable d_turnaround_within_1_year relative to the two random variables randuni and randnorm and choose to further confirm our expectations stated in the introduction of *5. Discussion of the Robustness of the Results*. Indeed, the turnaround-model provides probabilities of turnaround, which are positively correlated with actual turnarounds.

We argue that the positive and strong correlation between the predicted and actual outcomes presents sufficient evidence of a relatively effective turnaround prediction model which can therefore be used to attempt an enhancement of the optimal investment strategy L90 found previously.

5.1.3 The turnaround-adjusted investment strategy

We now turn to testing the robustness of our third finding regarding the turnaround adjustments to L90. Having defended, in the preceding sections, the results of utilizing the optimal investment strategy L90 out-of-sample along with the predictive accuracy of our turnaround prediction model, the next logical step is to combine these findings. In-sample, we attempted to improve the results of the optimal investment strategy by implementing a turnaround-adjustment. This adjustment sought to exclude a part of the relatively distressed companies from the investment portfolio, specifically, the companies with low probabilities of turnaround. In-sample we found that we were not able to improve the alpha of the optimal investment strategy, but we were able to improve the Sharpe ratio at the cost of a reduction of the investment alpha. The adjustment that was made to produce these results was to exclude the 10% of distressed companies in which we invest that had the lowest probabilities of turnaround. As we pointed out in-sample, we would like to test further adjustments out-of-sample - not only the 10%-adjustment just described. Indeed, we want to test whether 25%- 50%- 75%- and 90%-adjustments can enhance the investment alpha of the optimal portfolio. The reason we did not test these additional adjustments in-sample was that the amount of observations was questionably low. However, there is much more available data out-of-sample, which makes the adjustments possible. We therefore run these adjustments on both the portfolio that includes the financial crisis and the one that excludes the financial crisis. To make sure that the potential improvements to the optimal investment strategy stem from the addition of the turnaround-adjustment, rather than from limiting the observations to those companies on which we have enough data for us to calculate the probability of turnaround, we once again construct a benchmark portfolio. The benchmark portfolio is constructed using the original L90 strategy but limiting the market in which the investor can buy and sell stocks only to those stocks that have the variables necessary to calculate probability of turnaround readily available. The benchmark portfolio is constructed for both time periods and the portfolios are called L90_OOS_07_18_Bench and L90_OOS_11_18_Bench respectively. Both portfolios are very similar to those constructed without the limitation imposed on the market - L90_OOS_07_18 and L90_OOS_11_18. This indicates that the necessary data is available for a large portion of our out-of-sample data. Due to a larger number of observations, we have been able to include an extra portfolio adjustment in our out-of-sample analysis, investigated through the portfolios L90Top10_07_18 and L90Top10_11_18. These portfolios only invest in the 10% of distressed stocks that are most likely to perform a turnaround within one year from the time of investment. The results of the turnaround-adjusted portfolios are presented in Appendices U and V.

The two parameters used to measure whether an improvement has happened are the five-factor alpha and the Sharpe ratio. If we first look at the investment portfolios which include the crisis, we see that the investment alpha is positive for all adjusted portfolios. However, none of the adjusted portfolios have improved when comparing them to the benchmark portfolio. When looking into the different components of the alpha, it becomes clear, why no improvement has occurred. First of all, the excess return on the portfolios is lower for all the adjusted portfolios. There seems to be a pattern of negative correlation between the improvement of turnaround probability and the excess return. Some of the deterioration in excess return is matched by decreasing values of the factor loadings SMB, CMA and RMW. We also see a decrease in the factor loading connected to the excess return on the market This decrease is however only present when L90Top10_07_18 is compared to the benchmark portfolio. These effects would be expected to increase the alpha, since they are all values that are timed with the respective premia and then subtracted from the excess return. The last factor loading HML does not seem to depict a specific pattern. The factor loadings for L90Top50_07_18 and L90Top25_07_18 are both higher than those of the benchmark portfolio, whereas the rest of the adjusted portfolios are lower. The summary statistics for Excess return on market, SMB, HML, CMA and RMW in the period 2007-2018 are summarized in Appendix I. All variables have been converted to the premium over twelve months as described in *3. Methodology.*

As can be seen, the only variable that, on average, has a negative value is HML. Since all the other values are positive on average, the reported general pattern of the portfolio adjustments leading to a diminishment of the factor loadings should positively affect the portfolio alpha. Specifically, the factor loading for excess return is higher for L90Top90_07_18, L90Top90_07_18 and L90_Top90_07_18, compared to the benchmark portfolio. This reduces the alpha by quite a margin since the excess return on the market, on average, is a lot higher than the excess return on the other factors. The portfolio, which arguably should increase the alpha the most when only looking at the factor loadings is L90Top10_07_18, since this portfolio has the lowest factor loading for all factors. However, the resulting effect on the alpha is more than cancelled out by the large reduction in yearly returns on the portfolio. This in general seems to be true for all the portfolios. The positive effect on alpha that may come from the reduction in factor loadings is more than cancelled out by the reduction in yearly returns.

The next parameter we look at is the Sharpe ratios of the portfolios. We are still only looking at the portfolios which include the crisis. None of the portfolios improve the Sharpe ratio of the benchmark portfolio. This is in contrast to the in-sample results, which showed an improvement in Sharpe ratio when removing the 10% of stocks with the lowest probability of turnaround. All the adjusted portfolios have Sharpe ratios that hover around 0.66, except for L90Top10_07_18, which has a Sharpe ratio of 0.4083, far lower than the other portfolios. These results suggest that none of the adjusted portfolios should be preferred to the benchmark portfolio which has a Sharpe ratio of 0.763. As was the case with the portfolio alphas, the reduction in Sharpe ratio stems from the reduction in yearly returns of the portfolios. All but one of the turnaround-adjusted portfolios have a standard deviation, which is lower than that of the benchmark. Ceteris paribus, a low standard deviation results in a high Sharpe ratio. However, for all the adjusted portfolios, the positive effect of the reduction in standard deviation is countered by the negative effect of the drop in yearly returns.

Altogether, we can conclude that a turnaround-adjustment to the portfolio does not improve the results the investment strategy produces when including the financial crisis.

If we disregard the financial crisis and instead focus on the period 2011-2018, a similar pattern evolves as the one found in the period including the crisis. The investment alpha is not improved in any of the adjusted portfolios. This is most likely due to a similar pattern in the factor loadings. Summary statistics for the factors used in the five-factor model, limited to the investment period 2011-2018 are displayed in Appendix J. Only observations from 2011-2018 are included.

Note that three of the factors now average to a negative value. This means that positive factor loadings for these factors on average have a positive impact on the alpha. The three factors whose averages are negative are, however, extremely close to zero as well as having modest standard deviations of around 0.06. Despite a similar pattern, the factor loadings are all less extreme than the ones found when including the crisis, which suggests a lower volatility of the portfolio related to the factors of the five-factor model. One factor loading that does stand out as having a different pattern from the one we saw in the period 2007-2018 is the loading on HML. We now see a strictly increasing pattern from L90Top90_11_18 to L90Top25_11_18. L90Top10_11_18 has approximately the same loading as L90Top25_11_18. Of the five turnaround-adjusted portfolios, only L90Top90_11_18 has a lower loading than the benchmark portfolio.

This pattern suggests that relatively distressed companies with high probabilities of turnaround have higher loadings on HML, meaning that more of their excess returns can be explained by the value premium described in the five-factor model. The value premium, however, was one of the factors that was found to have a negative average and be extremely close to zero in the period 2011-2018. The effect of the increase in the factor loading on HML is therefore very low, and might actually make the alpha even less explained, as negative values increase the alpha. Another point to remember at this stage is that Fama and French (2015) found HML to be largely insignificant when extending the model to five factors. We have chosen to keep the factor in this paper, as it originally was included to explain the excess return on relatively distressed stocks (Fama & French, 1996).

When looking at the other factor loadings, the loadings on SMB and CMA both yield increasingly negative values (Appendix V). Both SMB and CMA are both on average negative (Appendix J). However, they are extremely close to zero, and their standard deviation as well as maximum and minimum values suggest that both positive and negative values can be found during the period for each factor. From the data presented here though, the combination of an average loading on SMB and CMA with negative values as well as average negative values of the factors should on average yield a positive product. Such a positive product should diminish the alpha, which, combined with the decrease in excess return, could be an explanation for the strictly decreasing pattern in the alpha.

If we look at the second investment performance parameter - the Sharpe ratio - it is difficult to make out a pattern when looking outside the crisis. In general, the Sharpe ratios are higher outside the crisis. This could be expected as the stock volatilities during crises are expected to rise, which in turn lowers the Sharpe ratio. Additionally, a crisis generally creates lower returns which decreases the Sharpe ratio further. The higher Sharpe ratios also creates the first improvement we see out-of-sample. The portfolio L90Top25_11_18, which only includes the 25% of stocks with the highest probability of performing a turnaround, produces a Sharpe ratio of 0.8779, compared to the Sharpe ratio of the benchmark portfolio 0.8300. Since the excess return of the portfolio has decreased from 0.6419 to 0.4390, the improvement in Sharpe ratio must stem necessarily from a reduction in standard deviation. The standard deviation drops from 0.7733 to 0.5001. This increase in alpha comes, as it did in-sample, at a cost. The tradeoff for an increase in Sharpe ratio of 0.0479 is a reduction in the five-factor alpha of 0.1919.

The results of this out-of-sample test of the turnaround-adjusted investment strategy show, that when including the financial crisis in the investment period, the actual results of the investment strategy are only worsened by taking the turnaround probability into account. When looking at a time period without the crisis, the turnaround-adjustment of only investing in the 25% of companies with the highest probability of turnaround produces a better Sharpe ratio than the benchmark portfolio with no adjustments. This improvement in Sharpe ratio was also observed in-sample, but with another cutoff point. In-sample, the improved Sharpe ratio was observed when investing in the 90% of companies with the highest Sharpe ratio.

5.1.4 Subchapter summary

From the lack of improvement in alpha, the fact that only the Sharpe ratio was improved both in-sample and out-of-sample and the fact that this improvement happened at different cutoff points, we conclude that extending the investment strategy L90 with a turnaround prediction model does not consistently nor significantly improve the results of the strategy. Instead, the adjusted portfolios seem to yield worse results. This is not in line with the expectations we presented in our Out-of-Sample introduction. Picking the 90% of relatively distressed stocks with the highest probability of turnaround each year will improve the Sharpe ratio of the investment portfolio, but will diminish the investment alpha".

The patterns in the investment alphas of the portfolio suggest the opposite of our original hypothesis H3 in *1. Introduction*, and this hypothesis is therefore rejected out-of-sample (just as it was rejected in-sample *4.4.1 Summary – PARTS 3 & 4*).

Instead, we find the opposite to be true, namely: The higher the probability of turnaround, the lower the alpha. From this, we will conclude that the probabilities of turnaround are already taken into account in the pricing of the stocks.

In *4.2.3 Summary – PART 2*, we argued that distressed companies in general are undervalued, which was further confirmed with the out-of-sample testing of L90. The out-of-sample results of our turnaround-adjusted portfolios further supports this statement. Arguably, a company with a high probability of failure in one year and a low probability of turnaround within that year must be said to be more risky than a company with a higher probability of turnaround. The results of the investment strategies suggest that these stocks are the ones that add most to the alpha of the portfolios, since the alpha is lowered when the probability of turnaround increases.

5.2 Realism of the investment strategies

The investment strategy L90 has proven itself both in sample and more so out-of-sample to produce an alpha. In this section of the paper, we will try to look more closely at this alpha and discuss whether it is possible to replicate it in real life.

Our evaluation of abnormal returns in this paper is based on the important assumption of absence of market frictions, meaning that there are no transaction costs and that investing in a stock does not affect its price. If such frictions were to exist, we would expect different results. In the following, we illustrate how a combination of aforementioned frictions might explain a portion of the investment alphas.

If we first look at the transaction costs that have been ignored in our out-of-sample results, the number of different stocks that have to be purchased (and sold) ultimo January each year is quite high. For now, we assume that we sell and repurchase the portfolio each year. This is not unlikely, as it has to be restructured in order for stocks to be equally weighted, as this is how we have calculated the returns. The number of stocks purchased each year in the period 2007-2018 are shown in Appendix K. Note that the table only shows 2007-2017, because the last purchase was made in January 2017. However, the last sale of stocks would be made January 2018.

If we assume that we sell all stocks at the end of the year to buy new ones, the total number of transactions would be at least 452 (January 2008). In a real-world scenario, there would be administration and transaction costs associated with these trades. That said, such costs would be unlikely to cancel out the entirety of the investment alpha of 0.4396 that was found for this period. In other words, even after accounting for transaction costs, we would still expect a positive alpha.

A far more important critique of the effectiveness of the L90 portfolio relates to the assumption that stock prices remain unaffected by transactions. As was noted in the analysis, the companies that are relatively distressed are, on average, companies with a very low market value of equity. In reality, this low market capitalization will have a huge impact on the investment strategy. Using the example of L90 this effect will be illustrated below.

Say an investment fund is willing to invest \$400 mil. in L90 in the period 2007-2018 (last sale of stocks occurs ultimo January 2018). We initially ignore the fact that the amount of invested capital each year will vary with the returns of the portfolio, but instead assume that \$400 mil. will be invested in the 10% of stocks that are most risky each year. As the market capitalizations of the companies in the portfolio are quite low, a relatively large chunk of the companies must be bought each year.

Appendix K shows the number of stocks invested in for each year, the sum of the market capitalization of all these companies, and the percentage of companies that are to be purchased.

The last column shows how large a part of each company that needs to be purchased in the portfolio, on average. If we only invest $400 million each year, we will have to buy on average between 2.7% and 4.2% of the companies we invest in. This purchase of stocks has to be done in January each year at approximately the same time, which is unrealistic. To illustrate why, we will use the year 2014 as an example. We have to find, on average, 3.8% of shares in the companies that are for sale at the current market price. If we want to make such a large purchase in such a short period of time, the assumption that this does not affect the price of stocks, and therefore the eventual return of the portfolio, is highly unlikely to hold. Additionally, these calculations do not take the accumulation of yearly returns into consideration. As can be seen in Appendix T, the average yearly return of the portfolio in this period is 0.5542. If we assume that we invest $400 million in L90 in 2010 and that for 2010 and 2011 the return of L90 is approximated adequately by the average for the period 2007-2018 (last sale of stocks occurs ultimo January 2018), we will see the following pattern: In January 2010 we invest $400 million and purchase, on average, 3.8% of each company. In January 2011 we would have $621.68 million in L90. We would then have to buy 5.357% of the companies, on average. In 2012 we would have $966.22 million to invest. For our stock purchase in January 2012, we would now have to purchase 8.753% of the equity of the companies. This pattern combined with the ability to purchase the stocks without moving the price within a very short time span seems completely incompatible with how the markets function in reality. Because of these factors, it would not be possible to take advantage of accumulated returns using this investment strategy if the size of the invested capital approaches a point where the investments would affect the stock prices. There is therefore a clear threshold as to how much can be invested in this strategy. Not just by one company, but by all investors in the market. If we say that under the circumstances that all shares have to be bought by the end of January, it is possible to purchase 1% of a company without moving the share price, the maximum amount that can be invested in this strategy would be $47 mil. 1% is an arbitrary choice of cutoff point to illustrate the extremely low market capitalization of the companies in the portfolio. It is important to note a bias in these calculations. As the data we perform these computations on are winsorized, the average market value of equity of the relatively distressed companies is biased in a positive direction. The real value of the average is lower than the reported total market capitalization reported in Appendix K, which only makes the above reasoning more potent.

We therefore argue that for large institutional investors, the fact that there is a low cap of how much can be invested in the optimal L90 strategy as well as a lack of accumulated returns makes the investment strategy unattractive when taking into account market frictions. This could very well be one of the reasons why the values of companies are not adjusted by market makers and why they remain undervalued. Campbell et al. (2008) completely neglected the effect of market frictions on their portfolio returns. Therefore, the abnormal returns reported by Campbell et al. might be heavily affected by these factors as well.

5.3 Testing for functional form misspecification

When developing optimal models for predicting corporate failure and turnaround, we expose ourselves to a potential functional form misspecification. This relates to Assumption 2 of the binary logistic model, in which we assume that there is a linear relationship between our covariates and the log-odds of the dependent dummy variable being equal to one. However, it is possible that even if our covariates do not satisfy this assumption, higher powers of these covariates do. We can investigate whether this is the case either by including several of the higher powers of the covariates 'by hand' or by running a formal test. In an OLS-regression, a common test is known as the Regression Equation Specification Error Test. In a logit regression conducted on the basis of a maximum likelihood estimation, a similar test is available, called the link test. This test builds on the work of Tukey (1949) and was elaborated further by Pregibon (1980). In essence, if the logit equation has been specified properly, it should not be possible to find additional covariates that are statistically significant, except by chance. Hence, the link test evaluates whether the addition of all the squared covariates to the equation is statistically significant. If so, the test suggests that our logit equation has been misspecified. To establish whether our logit equations were specified correctly, we proceed in the following, to conduct first a link test of our optimal failure prediction model. Subsequently, we conduct a link test of our optimal turnaround prediction model.

5.3.1 Link test – Failure prediction model

Let $y = f(\boldsymbol{X\beta})$, where $\boldsymbol{X}$ is a vector of covariates and $\boldsymbol{\beta}$ is the corresponding true parameters. $\widehat{\boldsymbol{\beta}}$ is then the set of parameters estimated through the logit-regression. The link test calculates _hat= $\mathbf{X}\widehat{\boldsymbol{\beta}}$ and _hatsq = _hat^2. We implement the link test in Stata, which yields the following output:

Figure 8 – Link test: failure prediction model

Logistic regression		
Number of obs	=	659,846
LR chi2(2)	=	1287.18
Prob > chi2	=	0.0000
Pseudo R2	=	0.1961

d_bankrupt	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
_hat	-0.434	0.256	-1.700	0.090	-0.937	0.068
_hatsq	-0.116	0.021	-5.580	0.000	-0.157	-0.076
_cons	-4.145	0.766	-5.410	0.000	-5.646	-2.645

Note: This figure presents the results of running a link test in Stata on our failure prediction model previously defined. D_bankrupt is a dummy which takes on the value 1 if the firm was delisted by the Center for Research in Security Prices with one of the following delisting codes: 552, 560 or 574. _hat is the multiplication of the vector of failure covariates **X** and the corresponding estimated parameters $\hat{\boldsymbol{\beta}}$. _hatsq is the squared value of _hat. _cons is the constant of this particular regression.

Source: Own computation through Stata 15.

As _hatsq is highly significant at any common significance level, this suggests that the squared covariates do carry statistical explanatory power when forecasting failure in one year. Note also that _hat (corresponding our original set of covariates) is only marginally significant at a 10% level. Moreover, the model which incorporates both the original set of covariates and their squared values yields a pseudo R-squared of 0.1961 which is superior to the one found when using only the original set of covariates (0.1900). In other words, there is evidence of our failure prediction model being misspecified.

Nevertheless, the squared covariates' significance might yield little economic interpretation value. To illustrate why, we manually generate all the quadratic terms and include them in the logit regression. The output is not presented here, but an example of how to interpret the parameter estimate of one of the quadratic terms follows. For instance, the squared liquidity ratio (L12_CASHMTA_sq) yields a positive and statistically significant parameter estimate. This would mean that the effect of liquidity on failure is exponential. Put differently, the more the liquidity ratio increases, the bigger the probability of failure. It goes without saying that we would have expected the opposite since we view liquidity as a healthy characteristic (which is also confirmed by the negative sign of the non-quadratic covariate L12_CASHMTA). Thus, the link test implies that it might be a good idea to include the squared liquidity ratio in our model, but we cannot attribute a logical reason as to why the relationship would be exponential. Therefore it seems more reasonable to omit the quadratic term from our failure prediction model though it could have increased our pseudo R-squared from 0.1900 to 0.1905.

To our knowledge, Campbell et al. (2008) did not run such specification test. At least, they did not report the results of it and they did not include any quadratic (or higher order) terms in their failure prediction model. Hence, for the purpose of replicating their paper as accurately as possible, we likewise did not alter our model despite it failing the link test.

On a last note, the economic interpretation becomes even more complex when including higher powers, such as the cubed or quartic covariates. Exploratory regressions suggested that the inclusion of some cubed covariates would yield statistically significant estimates while increasing pseudo R-squared. Other transformations such as the logarithmic or exponential transformation of a covariate could also potentially enhance the explanatory power of our failure prediction model. However, for all the reasons mentioned in this chapter, we proceeded with the failure prediction model as presented in Appendix G, aware of its potential misspecification.

5.3.2 Link test – Turnaround prediction model

In the same spirit, we further tested the robustness of our turnaround prediction model specification. The output of the link test is presented below:

Figure 9 – Link test: turnaround prediction model

Logistic regression

Number of obs	=	13,612
LR chi2(2)	=	2448.93
Prob > chi2	=	0.0000
Pseudo R2	=	0.1361

d_turnaround_10_within_1_year	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
_hat	0.998	0.031	31.950	0.000	0.937	1.060
_hatsq	-0.001	0.019	-0.070	0.941	-0.039	0.036
_cons	0.001	0.023	0.030	0.979	-0.045	0.046

Note: This figure presents the results of running a link test in Stata on our turnaround prediction model previously defined. D_turnaround_10_within_1_year is a dummy that takes on the value 1 if the firm experiences a turnaround within the following year (i.e. it exits the highest decile when firms are ranked according to their predicted probabilities of failure). _hat is the multiplication of the vector of turnaround covariates $\mathbf{X}$ and the corresponding estimated parameters $\boldsymbol{\widehat{\beta}}$. _hatsq is the squared value of _hat. _cons is the constant of this particular regression.

Source: Own computation through Stata 15.

As _hat is highly significant at any common significance level, while _hatsq is highly insignificant, we were satisfied with our turnaround prediction model specification and proceeded with no alterations.

6. Limitations

Despite conducting several robustness checks, we now turn to address some limitations of our research design before concluding. Although the following limitations have been addressed throughout this paper when relevant, the purpose of this chapter is to provide a succinct overview. Note that none of the limitations presented here were explicitly addressed by Campbell et al. (2008), despite their relevance.

6.1 Sample bias

Due to data availability, we ended up with less overall data points than Campbell et al. (2008). Consequently, we could not create the stock volatility variable in exactly the same way as Campbell et al. (2008). That said, expectedly the difference between our measure of volatility and that of Campbell et al. (2008) was small order of magnitude (cf. *3. Methodology*).

When conducting our review of the extant literature, we noted a significant bias of samples stemming from the United States and the United Kingdom. However, since data was more readily available for the US, this paper did not contribute to closing the empirical gap in sample origins.

6.2 Relative definitions of distress and turnaround

Both our definition of distress and turnaround are relative to the rest of the companies in the dataset. This yields a limitation to the certainty of our findings for the following reasons. First, since the definition is relative, we could have in theory a situation where all but one company has a probability of failure of 0.001%. If the last company then has a probability of failure of 0.002%, this company would, using our definition, be distressed. It is therefore important, when interpreting the results of this paper, to keep this in mind. The second shortcoming of the relative definitions are the pre-specified number of companies that can be distressed (see *3.4 Measures of failure, distress and turnaround*).

6.3 Selection bias

In addition to the sampling bias, our arbitrary definitions of distress and turnaround entail a certain selection bias. Our definition of distress is arbitrary in that (1) we picked the specific delisting codes from CRPS which we deemed equivalent to failure, (2) we defined the prediction period of failure as one year into the future, (3) we defined distress of one firm as a relative measure to the overall pool of sampled firms. Due to the symmetrical nature of our definition of turnaround relative to distress, the same biases follow, with the small difference that when predicting turnaround, we defined the event as happening *within* the following year, and not in one year.

6.4 Censoring bias

In dynamic logit models such as ours, if a firm were to leave our sample for any other reason than failure, they will be considered censored. This differs from static models in which such firms would simply be assumed healthy. To understand the type of censoring, let us look at a few examples. For instance, if a firm were to merge with another for reasons *unrelated* to its probability of failure, we would consider this case as non-informative censoring. Non-informative relates to the information regarding the firm's risk of failure. Contrarily, if a firm were to merge with another for reasons *related* to its probability of failure, we would consider this case as informative censoring. In the case of non-informative censoring, our model estimates would not be biased, as the censoring has nothing to do with the given firm's probability of failure. However, in the case of informative censoring, our model estimates would be exposed to a potentially serious bias.

In this regard, we remind the reader that our firm-specific data was collected from the COMPUSTAT and CRSP databases. If looking at our sample as a whole, 9796 out of 14588 firms were present throughout the whole collection period. Since our dataset only contains 476 failures, 4316[8] firms left the sample for reasons other than failure. As we have arbitrarily defined failure as the corresponding delisting code being equal to 552, 560 or 574, by construction, we assume that these 'other reasons' (i.e. delisting codes equal to other numbers than aforementioned) are completely unrelated to failure. Thus, our sample is expected to contain no censoring bias. However, if our understanding is flawed regarding the specific delisting codes and their relation to failure, then our failure prediction model developed later on might be subject to a censoring bias, in which case the estimates would not be trustworthy.

6.5 Misspecification bias

For reasons mentioned in *3.6 Quantitative Method*, our models of failure and turnaround might have been subject to misspecification bias. We addressed this issue by performing link tests for model specification

[8] 4316 = 14588 – 9796 – 476

after running the regressions in Stata. We found that the failure prediction model would have a higher explanatory power if the covariates were included along with their squared and cubed values. Nevertheless, the squared and cubed covariates might have little economic sense. Moreover, Campbell et al. (2008) did not include those terms in their failure prediction model, hence for the purpose of replicating their paper, we likewise proceeded without including them. However, duly noting that their model might be subject to a misspecification bias. Lastly, we also ran a functional form test on our final turnaround prediction model, which showed no evidence of model misspecification.

6.6 Omitted variable bias

As in any other empirical study, causality needs to be assessed. It is quite conceivable that our models of failure and turnaround do not include all relevant predictors, simply because our literature review yielded no single superior consensus set of covariates explaining failure or turnaround. If any of the omitted predictors are correlated with the included covariates, this would cause our estimates to be biased. However, there exists no formal test to check for omitted variable bias – one simply needs to rely on economic intuition.

6.7 Reverse causality

Even if our models of failure and turnaround were to accurately yield causal inferences, the potential problem of reverse causality merits a short review. When developing our dynamic logit models, we operated under the implicit assumption that changes in our set of covariates could explain the changes in distress or turnaround. However, it might be the other way around, i.e. that changes in distress or turnaround are the cause of changes in our covariates rather than the consequence. Again, we can rely only on our economic intuition to defend our model construction, as there exists no formal test to investigate the problem of reverse causality.

6.8 Friction-free assumption

A final limitation that we wish to address is that when evaluating portfolio returns on the basis of a Fama-French factor model, we inherently assume a frictionless market. In essence, a frictionless market is one where all transaction costs and other restraints are non-existent. For instance, there is no costs associated with purchasing or selling a stock; there is no taxes paid on capital gains earned from holding a stock; and there is no limit to how much we can go long or short in the given stock. To investigate the effect of partly freeing one-self from this friction-free assumption, we restricted investments in each stock to a maximum of one percent. This yielded a maximum investment capacity in our investment portfolio of 48 million dollars. If we were to include the effect of taxes and brokerage costs, this number would fall. Hence, although this paper provides investors with a profitable trading strategy, it is important to understand its limits when implementing it into the real world.

7. Conclusion

The research question that we have sought to investigate in this paper had two main parts: Can a profitable investment strategy be generated from modelled probabilities of failure?; and can we improve this strategy by adjusting it according to modelled probabilities of turnaround? We constructed our models on data from 1963-2004 and tested the findings out-of-sample with data from 2007-2018.

The first section of the analysis focused on the replication of the failure prediction model from *In Search of Distress Risk* (Campbell, Hilscher, & Szilagyi, 2008). We approached data collection and manipulation in a similar manner to Campbell et al. but made adjustments where necessary due to lack of data, and most importantly, we chose a different definition of failure, thereby also entailing a different classification of distressed and turnaround firms, despite adopting the same classification methodology. That said, our dynamic logit failure prediction model is, in most respects, similar to the one presented by Campbell et al. (2008). All but one coefficient have the same sign and the general significance of the covariates is likewise similar to those of Campbell et al. In our results, however, we find the variables TLMTA and NIMTAAVG to be statistically insignificant whereas they were significant in Campbell et al.'s model. On the other hand, we find PRICE to be statistically significant, whereas Campbell et al. did not. These differences may point to a potential interplay between selected covariates. Indeed, we did find some non-negligible correlations among covariates but these are not considered to be alarming. Altogether, we conclude that the failure prediction model of Campbell et al. is replicable.

On this basis, we used our replica failure prediction model to investigate the research questions of the paper, focusing our analysis on the employability of our model as a stock picking tool. In this regard, we developed **seven** investment portfolios which, in different variations, were constituted of long and/or short positions in distressed stocks. Our **first two portfolios** mimicked the optimal investment strategies found by Campbell et al. Their results suggested that by going long in stocks with relatively low predicted probabilities of failure while shorting those with relatively high predicted probabilities of failure, one would be able to consistently beat the market by several percentage points. Despite having replicated Campbell et al. (2008)'s failure prediction model, we were in no way able to replicate the returns of Campbell et al.'s investment strategies nor to confirm their optimal strategy. Additionally, we developed **two robustness portfolios** based on the coefficients of the failure-predicting model created by Campbell et al. These two portfolios were constructed in order to test whether the discrepancies between our portfolio returns and those of Campbell et al. stemmed from the different parameter estimates found in the failure prediction model. We concluded that this was not the case. We then continued our analysis by constructing **portfolios 3 and 4**, in which we invested oppositely to the first two portfolios. Portfolios 3 and 4 went long in stocks with relatively high predicted probabilities of failure while shorting those with relatively low predicted probabilities of failure. The returns were improved significantly, yet driven only by the long portion of the portfolios (3 and 4). This led us to defining **our final and optimal investment portfolio** L90 as the one that went long in companies belonging to the highest decile when ranked according to their predicted probabilities of failure. According to the five-factor model developed by Fama and French (2015), L90 generated an average investment alpha of 5.54% over the period 1973-2004. When testing this strategy out of sample it still delivered abnormal returns, both when including and excluding the financial crisis of 2008.

Having identified our optimal investment portfolio, we explored the second part of our research question, attempting to improve the profitability of L90 further by adjusting the stock-picking process to take account of probabilities of turnaround. The first natural step herein was to develop a theoretically sound and empirically accurate turnaround prediction model. Inspired by the extant literature on corporate turnaround, we defined twelve relevant covariates based on company financials. Additionally, to our knowledge, we made a unique contribution to the literature by adding a set of time dummies that describe how long a company has been in a distressed state. Our model's ability to predict turnarounds within one year was tested out-of-sample, where the predictions were found to have a correlation of 55% with the actual turnarounds. From this, we conclude that our developed model is relatively effective at predicting turnarounds within one year.

Our final step was then to implement the predicted turnaround probabilities in the stock-picking process. The optimal portfolio L90 meant going long in distressed stocks. Therefore, the idea was to adjust L90 by going long only in those distressed stocks that had high probabilities of experiencing a turnaround. To define which cut-off point to use to delimit 'high probabilities of turnaround', we experimented with the top 90%, top 75%, top 50%, top 25%, and top 10%. In-sample, we were able to improve the Sharpe ratio of L90 by excluding the 10 percent of stocks that have the lowest probability of turnaround (i.e. using top 90% as a cut-off point). However, this result was not replicable out-of-sample, neither with nor without the financial crisis included in the sample period. Furthermore, all of our turnaround-adjusted portfolios underperformed relative to the unadjusted portfolio L90 when strictly looking at the five-factor alpha, both in-sample and out-of-sample. We therefore conclude that although our turnaround model is found to accurately predict the occurrence of turnarounds, our relating portfolio adjustments have no significant impact on the portfolio returns. Consequently, the unadjusted L90 remains the optimal investment portfolio.

We propose two key explanations to the abnormal returns generated by L90: First, companies that are relatively distressed compared to the rest of the market are in general undervalued, and an abnormal return can be gained from investing in them. The fact that these returns diminish when excluding from the portfolio firms that have low probabilities of turnaround suggests that the more distressed a company is, the more undervalued it is. Campbell et al. likewise supported the existence of a distress risk premium, however to be collected by shorting the distressed companies rather than longing them. That is, they found evidence that distressed companies were overvalued. This discrepancy in results might be explained by the second justification of the existence of abnormal returns. Indeed, a reason why L90 has not been utilized more in the real world could be that the underlying assumption of a friction-free market does not hold outside the theoretical world. If limiting the amount that can be invested in each company without affecting the price of the given stock, the total value that can be invested in L90 by the entire market becomes negligible when considering large institutional investors. We further have to consider that there needs to be a willing investor to buy or sell the stock. Additionally, transaction costs and other market frictions will lower the returns generated by L90 even further. We can therefore not confidently conclude that L90 is a profitable investment strategy in a real-world setting. Similarly, we cannot confidently believe in the abnormal returns reported by Campbell et al, since they likewise relied on the assumption of a friction-free market.

We set out to test three hypotheses of which we were able to confirm the first (H1), while H2 and H3 were rejected. H1 related to the replicability of the failure prediction model of Campbell et al. and as explained above we found it to be replicable. H2 aimed to test the replicability of the returns of Campbell et al.'s investment strategies, which we were not able to replicate. With H3 we wanted to test if modelled turnaround probabilities could be used to improve our investment strategy further. This idea was not supported by our results.

Although we were able to demonstrate that modelled probabilities of failure can be used to generate a profitable investment strategy *in theory*, our analysis showed that the abnormal returns found are unlikely to hold *in the real world*, due to market frictions that will have an impact on the yield.

8. Further research

8.1 Industry conditions

Our literature review suggested that, to some extent, the industry conditions matter when forecasting failure and turnaround. This paper did not focus on industry conditions, hence there might be a potential omitted variable bias if these were to be correlated with both our dependent variables (failure and turnaround) and our covariates. Further research could therefore focus on including such industry proxies when modelling failure and turnaround.

8.2 Correlations among covariates

Both our failure and turnaround prediction models depicted non-negligible correlations among selected covariates. This might lead to a violation of Assumption 4 as set out in the *Binary logistic model assumptions*. The issue deserves further investigation.

8.3 Time spent in distress

When developing our optimal turnaround prediction model, we found that time spent in distress is a significant predictor of the occurrence of turnarounds. Although seemingly intuitive, we have encountered little research mentioning this factor, and no research that explicitly includes this factor in its modelling. We therefore encourage further research to take our findings into account.

8.4 Distress Factor

In this paper, we presented empirical evidence of the existence of a distress risk premium. In the following, we describe how one would be able to quantify this risk premium for the purpose of confirming its existence in further studies.

The factor HML, which was originally included in the three-factor model by Fama and French (1996) to explain high return for relatively distressed companies, does not seem to capture the higher returns of relatively distressed companies found using our predicted failure probabilities. Therefore, we suggest that an extra factor could be included in the Fama-French five-factor model. Let us call this extra factor Risky Minus Secure (RMS), representing the returns of risky companies minus the returns of secure companies. We would then need to estimate the associated beta and risk premium, which can be done through a

Fama-Macbeth two-step procedure (Fama & Macbeth, 1973). Although we will not complete this task in this paper, we will shortly explain how RMS should be constructed for the purpose of further research,.

The first step would be to run a time-series regression of each stock i's excess return on the five Fama-French factors:

$$R_{i,t} = Rf_{i,t} + \beta_{i,MktRf}MktRf_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,CMA}CMA_t + \beta_{i,RMW}RMW_t + \beta_{i,RMS}RMS_t + \epsilon_{i,t}$$

The point of this step is to determine each stock's alpha and set of betas (i.e. $\alpha_{i,t}$; $\beta_{i,MktRf}$; $\beta_{i,SMB}$; $\beta_{i,HML}$; $\beta_{i,CMA}$; $\beta_{i,RMW}$; $\beta_{i,RMS}$).

The second step would be to run a cross-sectional regression for each month t of each stock i's excess return against the parameters estimated in step one:

$$R_{i,t} = \gamma_0 + Rf_{i,t} + \beta_{i,MktRf}MktRf_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,CMA}CMA_t + \beta_{i,RMW}RMW_t + \beta_{i,RMS}RMS_t + v_{i,t}$$

The point of this step is to determine each factor's risk premium (i.e. $MktRf_t$, SMB_t, HML_t, CMA_t, RMW_t, RMS_t). We achieve this by taking the arithmetic average of all of the premia found for each month.

Finally, we can test the statistical significance of our newly added factor RMS by using an estimate of the standard error (see page 617 in Fama & Macbeth, 1973). If the RMS were to be found statistically significant, this would speak for the existence of a distress risk premium. Strategic investors might collect this premium at their own benefit if market frictions would not hinder them sufficiently.

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