Three Papers in Empirical Finance and Accounting

by

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Wuppertal, August 2020 Steffen Möllenhoff

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1 Introduction

This first chapter aims to briefly summarize the three papers in this dissertation. While working at the University of Wuppertal as a research assistant, the studies summarized below were written with different co-authors in the last three years. The papers are sorted chronologically according to the date of the beginning of each research project.

Although the three studies were carried out independently of each other and do not tell a common story, they share some common characteristics in terms of methodology, content and theory. While each paper is an empirical study in the field of finance and accounting, the first two studies deal with the events of bankruptcy. The first study is primarily aimed at directly improving the prediction of corporate bankruptcies, the second study addresses the entire decision-making process of professional investors prior a corporate bankruptcy event, starting with the gathering of disclosed corporate information, the prediction of such events, and ending with stock sales activities in the run-up to a corporate bankruptcy. Although the third paper is a study in the field of corporate governance which examines the effects of “unwanted“ directors on the share price and operating performance of companies, the study deals with adverse corporate developments. Within an organizational structure, the directors’ job is to monitor and advise the management of the company’s management in order to protect the interests of shareholders and, in extreme cases, to prevent the bankruptcy of a company.

Additionally, the three studies share one common ground in terms of economic theory: the absence of an “informationally efficient market“ (Malkiel and Fama, 1970; Fama, 1991) and the fact that a perfectly efficient market where prices fully reflect all available information is unlikely to exist in practice, because no investors would have an incentive to bear the costs of acquiring and processing such information (Grossman and Stiglitz, 1980). If prices would fully reflect all available information, we would not have been able to improve corporate bankruptcy predictions, professional investors would not conduct more research on effectively bankrupt companies and start selling their share in those companies more than one year prior bankruptcy, neither shouldn’t director voting be informative for the future development of share prices and operating performance.

Paper 1: Nonlinear Relationships in Bankruptcy Prediction and Their Effect on the Total Cost of Misclassification: Empirical Evidence on Listed U.S. Companies

In order to derive a reliable prediction of bankruptcy, it is necessary to strike a balance between a model's validity and complexity. The study *Nonlinear Relationships in Bankruptcy Prediction and Their Effect on the Total Cost of Misclassification: Empirical Evidence on Listed U.S. Companies* extends commonly used bankruptcy prediction models by taking into account nonlinear relationships between independent variables and the predictor for the probability of bankruptcy.

Using data on 8.557 U.S. listed companies for the period from 2000 to 2017, we show that several independent variables used in prominent bankruptcy prediction models have statistically significant and economically plausible nonlinear effects on the probability of a company going bankrupt. In the value range where the independent variables exhibit sufficient data points, it is safe to assume that these variables have an almost linear effect on the predictor. However, we did observe nonlinear relationships below and above specific thresholds at which the estimated spline functions change their slope.

Omitting the effects of nonlinear relationships may distort the estimates of a company's probability of going bankrupt. This makes it necessary to evaluate the economic relevance of taking into account nonlinear relationships. For that purpose, it is important to select appropriate validity criteria.

The validity measures that are based on either likelihood or classification indicate that the validity of the *Generalized Additive Models* we used, in which we took into account nonlinear relationships, is higher than that of the equivalent *Generalized Linear Models.* As a result, we have to acknowledge that there are relevant nonlinear relationships between the independent variables and the predictor used in prominent bankruptcy prediction models. However, the improvements in the validity measures that are based either on likelihood or on classification may not necessarily be perceived as sufficient to justify choosing a more complex model for predicting bankruptcy. When only such measures are used, there is a risk that the evaluation of bankruptcy prediction models will lead to a wrong conclusion and to choosing an inappropriate model, even if that model reduces the total cost of misclassification on an economically relevant scale. For example, a global, single-item validity measure such as the AUC does not take into account the actual consequences and thus the total cost of misclassification. Consequently, single-item validity measures such as the AUC distort conclusions on validity. To prevent this, it is advisable to evaluate such models on the basis of practical relevant assumptions about the consequences of misclassification.

The study further examines whether the amount of reduction in the total cost of misclassification can serve as a further validity criterion. To demonstrate the validity of this criterion, we apply two nested models that differ only with respect to nonlinear relationships: the GAM takes them into account, while the GLM does not. Consequently, we can be confident that any reduction in the total cost of misclassification can be attributed to the inclusion or exclusion of existing nonlinear relationships. With respect to a range of plausible cost relations, we found that applying a GAM clearly reduces the total cost of misclassification in both the training and the validation sample. The increase in the validity of classification in terms of reducing this cost amounts up to 18.9% under assumptions that hold in practical applications.

The results of our analysis are limited by the specific failure criterion that we chose to apply, as well as by the low number of observations in the peripheral areas of the independent variables we examined. The failure criterion we chose relies on the definition of bankruptcy and the prediction horizon. We believe that it should be possible to replicate our results using different criteria of failure; however, further research is needed in order to confirm this supposition. Our study identified nonlinear relationships, particularly in the peripheral areas of the independent variables that we used. However, these nonlinear relationships are based on relatively few observations, so further research is needed in order to investigate whether the nonlinear effects that we identified also hold when different databases are used.

The results of our analysis are also limited by the deterministic and mean cost relations that we assumed. We based our analysis of the total cost of misclassification on given cost relations that are identical in all observations. However, the actual cost relation should be estimated separately for each observation. In the context of bank lending, the cost $C(1)$ results from the misclassification of companies that are actually bankrupt and should correspond to the estimated loss in the case of default. In comparison, quantifying the cost $C(0)$ that arises from the misclassification of companies that are actually solvent is a challenge, because this cost consists in foregone profits, reputational cost, and other opportunity costs. One problem is that the practical fitness of a specific bankruptcy-prediction model can only be evaluated on the basis of a validity measure that considers the total cost of misclassification, rather than a validity measure that is based exclusively on either likelihood or on classification. To resolve this problem, future research and future practical applications will need to examine whether more complex models for predicting bankruptcy also reduce the total cost of misclassification to an economically relevant extent.

Paper 2: Dark Premonitions: Pre-Bankruptcy Investor Attention and Behavior
Which market actors do gather and process disclosed company information to approximate the financial health of a company has remained a black box in the literature. The study *Dark Premonitions: Pre-Bankruptcy Investor Attention and Behavior* aims to open this black box to reveal the value of such information for investors and providing inside – on micro-level – which types of investors are able to decipher the information and subsequently reduce or avoid the portfolio impact of holdings in companies that will go bankrupt. To the best of our knowledge, no prior study documented the search behavior and subsequent trading activities of professional investors prior to a corporate bankruptcy. Revealing the entire process starting with gathering disclosed company information and ending with stock selling activities ahead of a corporate bankruptcy is the main contribution in this paper.

The EDGAR log-file data set used in this study contains detailed information on how market actors access disclosed company information from the EDGAR server and provides the opportunity to better understand the behaviour of professional investors. By identifying the partly anonymized IP addresses of 2,481 market actors as well as IT-companies and universities that request filings from the EDGAR database, we are able to identify approximately 40% of all requests (13.7 billion) and to differentiate between different groups of professional investors and other interest groups who search for disclosed company information. Furthermore, the identification of market actors made it possible to combine the EDGAR log-file dataset with data on investor holdings derived from Form 13F filings. Based on these data we conduct an empirical analysis not only on investor attention before a bankruptcy event occurs, but also on prior selling activities of professional investors.

Although different information gathering behavior of specific market actors contrasts with the "efficient market hypothesis", the obtained results are in line with economic theory and extent existing empirical research on investor attention: If the efficient market hypothesis is valid, stock prices should fully reflect all available information at any point in time. Gathering and processing information on a company should not lead market actors to gain significantly greater return than they would have done without this information (Malkiel and Fama, 1970; Fama, 1991). Therefore, the probability that a company will become bankrupt in the future should also be reflected in its stock price. As a result, gathering and processing public company information in order to predict a company's probability of bankruptcy on that company should be worthless for market actors.

However, according to Grossman and Stiglitz (1980), a perfectly efficient market where prices fully reflect all available information is unlikely to exist in practice, because no investors would have an incentive to bear the costs of acquiring and processing such information. Research is costly to investors (Grossman and Stiglitz, 1980; Lee and So, 2015; Verrecchia, 1982) and attention is a so-called constrained resource (Kahneman, 1973) that is allocated rationally by (skilled) investors to particular companies (Kacperczyk et al., 2016). As a result, investors should only bear the cost that information gathering and processing involve while this does not exceed the corresponding marginal return (Lee and So, 2015).

The assumption of perfect market efficiency, as these considerations suggest, is rather strict. For that reason, Campbell et al. (1997) proposed the idea of "relative efficiency." The authors argued that the degree of market efficiency is empirically observable and will vary over time (Kim et al., 2011). This line of thought was further developed into the "adaptive markets hypothesis" (Lo, 2004, 2019; Kim et al., 2011), which postulates that the degree of market efficiency fluctuates over time and is governed by market conditions. If the adaptive markets hypothesis is valid, there should be incentives for investors to acquire and process information in order to adapt and react to changing market conditions.

Market conditions of a company can particularly turn into a bad state. With regard to the change into a bad state already Samuelson (1938) argued that market actors acquire disclosed company information to reverse engineer their private expectations as gathering and processing information could ultimately reveal clues about the financial health of the companies in which these market actors are interested. More recent studies (e.g., Altman (1968), Campbell et al. (2008), Beneish (1999), Dechow et al. (2011), Seyhun and Bradley (1997) documented that disclosed company information such as accounting information and information on insider trading can be used to predict financial distress and corporate bankruptcies or to detect fraud. Given the assumption that some market actors have the skill to learn from disclosed company information (Kacperczyk et al., 2016), we follow that gathering and processing disclosed company information is a fundamental mechanism which helps market actors to adapt to a constantly changing environment and to prevent themselves from the financial impact of negative events such as bankruptcies. As a result, high losses associated with a bankruptcy event should increase the incentives for market actors to pay more attention to companies that are likely to become bankrupt in the near future than on companies that are unlikely to face bankruptcy in the foreseeable future.

This reasoning appears to be at odds with the findings of Drake et al. (2020). In their study on all US-listed companies, Drake et al. (2020) showed that professional investors tend to acquire more information on companies and stocks that perform better in the short term than on other companies. However, the sample that Drake et al. (2020) used is skewed towards companies that were likely to remain solvent, which means that their data may have failed to capture the unusual degree of attention investors paid to the companies that eventually went bankrupt.

Extending the empirical findings of Drake et al. (2020), we investigate how much attention professional investors pay to companies that are likely to declare bankruptcy in the near future. Our starting point is that if professional investors indeed focus more on such companies, then we should be able to observe how at least some investors translate the information they gather on such companies into action—in other words, how such information affects the decisions of investors to sell their stock in companies that are highly likely to go bankrupt in the near future. More specifically, we expect that skilled professional investors (Kacperczyk et al., 2016), who are better informed than others, are likely to reduce their shares in companies that are likely to go bankrupt but not in companies that, although financially distressed, will remain solvent. In this scenario, selling leads to positive excess returns in two ways: First, skilled professional investors will earn greater returns if they acquire information on companies that are effectively, though not yet officially, bankrupt than they would have done if they had not acted on the basis of such information. Second, these investors will achieve greater returns than unskilled or less skilled professional investors who only rely on free (and therefore limited), rather than paid (and therefore comprehensive) information on companies (Verrecchia, 1982). Market prices reflect the aggregated amount of information processed by all investors who were active during a given period. Such information, however, only becomes available in part and gradually (Verrecchia, 1982). For that reason, we expect that skilled professional investors start selling their shares in effectively, but not officially, bankrupt companies before stock prices start to decline.

Our analysis is primarily based on the log files of the EDGAR server that the Securities and Exchange Commission (SEC) maintains. These data include detailed information on server traffic; specifically, on requests made for information (e.g., on the volume of requests and the type of filing that was requested) on the SEC filings of US-listed companies in the period February 14th, 2003 to June 30th, 2017. From these data, we were able to collect information on a sample of 2,481 market actors who requested information on company filings held on the EDGAR database. Our analysis of the partly anonymized IP addresses of these actors enabled us to differentiate between investors and other types of actors, as well as between different categories of professional investors on the basis of various criteria, including geographical location. Furthermore, we took care to control for factors that could potentially influence the data (such as certain company characteristics or specific events that occurred in the period of interest) but are not related to bankruptcy.

Based on the applied data, we empirically document that market actors conduct significant more research on effectively bankrupt companies than on non-bankrupt peer companies that, although financially distressed, remain solvent. Furthermore, we provide empirical evidence that portfolio decisions go along with prior information gathering and processing. With respect to Drake et al. (2020) we extent the existing literature by analysing market actors' attention to effectively bankrupt companies and show that information gathering by professional investors is associated with a reduction in portfolio holdings of these companies.

The findings of this study contribute to the literature in two major ways: First, it sheds light on the attention investors pay to financially distressed companies. Second, it reveals that it is possible to predict bankruptcy more accurately by utilizing particular types of data. We found that professional investors who acquired extensive information on companies that eventually went bankrupt also reduced their holdings about one year before these companies declared bankruptcy. This indicates that certain professional investors, such as investment banks, hedge funds, and asset management companies, start reducing their holdings in companies that will eventually go bankrupt at an early stage, but not in companies that, although financially distressed, remain solvent. In sum, our analysis shows that it is possible to improve the accuracy of prediction models by introducing an explanatory variable that is based on either the amount of attention investors pay to a company or on the observable holdings professional investors have in a company.

Our findings also suggest that the information disclosed in Form 10-K and Form 10-Q filings, which account for about 21% of all requests submitted to the EDGAR server, can help investors assess a company's financial health and prospects. Although our analysis does not focus on these filings, there is no question that accounting information plays an important role in evaluating a company's financial health. Form 10-K and Form 10-Q filings are publicly available. However, it appears that only specific market actors are able to identify companies that are effectively bankrupt ahead of actual bankruptcy. This leads us to conclude that accounting expertise is highly valuable in the case of bankruptcy prediction.

Paper 3: Watch the votes: How unwanted directors hurt firm performance

In an organizational structure the directors' job is to monitor and advise the company's management in order to protect shareholders' interests. Poor director performance can have adverse effects for the company and thus for shareholders, e.g. if monitoring is weak, managers may engage in empire building to increase power and influence in the organization (Jensen, 1986), while in the absence of good advise managers are more likely to make value-destroying decisions (Renjie and Verwijmeren, 2019). As agency theory suggests, a well-functioning board of directors is, therefore, key to protect shareholders' interests (Masulis and Zhang, 2019). Given that shareholders express their satisfaction with the board of directors through voting at director elections (Chen and Guay, 2018), the study *Watch the votes: How unwanted directors hurt firm performance* addresses the question whether shareholder votings additionally give important insights about the level of monitoring and advising exerted by directors and are thus informative of future firm value.

Some recent studies have addressed the informational content of director election outcomes, but it remained unclear whether they are insightful for a firm's future value. While Chen and Guay (2018) state that director voting is a proxy for shareholders' satisfaction with directors, Cai et al. (2009) are sceptical with respect to the effectiveness of voting. Aggarwal et al. (2019) find that voting is an effective mechanism to bring about changes in a firm's corporate governance and board structure and that directors receiving more dissent votes have less opportunities in the director labor market, while Fos et al. (2018) find director elections to be a fundamental feature of corporate governance since they induce directors to monitor management more rigorously.

Regarding the relationship between the effectiveness of corporate governance and firm value, there are several studies showing firms with stronger corporate governance to be associated with higher firm value (for an overview, see Ammann et al., 2011). The rational being that firms with weaker governance face greater agency problems and thus more value-destroying behavior (Core et al., 1999). We argue that if director election results are informative of a director's abilities to monitor and advise management, we expect directors receiving less shareholder support to have a negative impact on firm performance. We assume the main information in receiving less votes than their peers is that they are less effective monitors and/or advisors in the eyes of shareholders.

By examining a large sample of 119,126 director election events between 2001 and 2018 and 30,564 firm-year observations respectively, we show firms with *unwanted* directors on the board, i.e. those with less votes for (re)election than their peers, to experience a significant decline in firm value and operating performance in the following 12 months. A one unit increase in the number of *unwanted* directors on a firm's board is on average associated with a decline in subsequent stock performance by 37 basis points p.a. and a decline in operating performance by 39 basis points p.a. The results are robust across various specifications, where we use different measures for stock market and operating performance as well as different measures of *unwantedness*. In particular, we find the number of unwanted directors on a firm's board to be the dominant driver of the decline in firm value and performance. While firms with only one *unwanted* director on the board do not experience a decline in subsequent firm performance, firms with two or more *unwanted* directors on the board do. Also, we find that directors who stayed *unwanted* in two consecutive years do not have an impact on stock market performance in the second year. Hence, this suggests that the market already accounts for the lack of monitoring and advising exerted by these directors in the first year. The results hold when controlling for a variety of firm characteristics, board characteristics and takeover defense mechanisms as well as when including various fixed effects.

We find evidence suggesting that firm performance is not negatively affected when there is only one *unwanted* director on a firm's board, however, having two or more *unwanted* directors on the board is associated with a decline in subsequent firm performance. Furthermore, we analyze if markets differentiate between *unwanted* directors who stayed *unwanted*, i.e. directors receiving significantly less shareholder support at two consecutive elections, and those who only receive significantly less shareholder support in one respective year. The results suggest that *unwanted* directors who stayed *unwanted* are not significant to subsequent stock market performance indicating that markets already account for *unwantedeness* when it first appears. Overall, our first set of results supports the view of shareholder voting outcomes being informative of the level and the effectiveness of monitoring and advising exerted by corporate directors.

To address concerns of endogeneity (Hermalin and Weisbach, 2003), we follow Nguyen and Nielsen (2010) by analyzing stock price reactions surrounding the sudden deaths of corporate directors. A major advantage of using this approach is that sudden deaths occur randomly and are independent of firm and board characteristics. Hence, this approach helps us to confirm a relationship between an individual director's voting results and firm value. Our results show both the percentage "for" votes a particular director receives as well as our definitions of *unwanted* directors to be statistically significantly related to the stock market reaction surrounding the sudden deaths. We find stock price reactions to sudden deaths of directors who receive more shareholder support to be more negative, while we find stock price reactions to sudden deaths of *unwanted* directors to be more positive, supporting our previous findings. Additionally, we employ a trading strategy to further shed light on the informational content of voting outcomes about subsequent firm performance. Using four different pair trading strategies based on stocks of firms with and without *unwanted* directors, we find support for our previous finding. We show selling stocks of firm's with a share of more than 60% of *unwanted* directors and buying equivalent firms without any *unwanted* directors on the board to earn an average return of 5.91% p.a. Since the number of *unwanted* directors on the firm's board matters, we find strategies focusing on firms with a smaller share of *unwanted* directors to be still profitable, but less so. To ensure that the results are not driven by riskiness or "style" factors, we run various regressions using the most common factors proposed in the literature (see e.g. Carhart, 1997; Fama and French, 1995, 2015) as independent variables. The results are consistent with what we found before. So the strategies focusing on firms with a share of more than 60% of *unwanted* directors on the board and equivalent firms earn a significant monthly alpha of at least 52 basis points.

Overall, the results contribute significantly to the existing literature and have several implications. In contrast to Cai et al. (2009) and Ertimur et al. (2018), we find that election outcomes are associated with subsequent firm performance. We also deepen the understanding of votes being informative of a director's ability to monitor and advise management efficiently (Aggarwal et al., 2019; Fos et al., 2018). Further, we contribute to the literature analyzing the value of individual directors as well as to literature examining the role of the board of directors on firm performance. Regarding implications, our results suggest that although director elections are considered routine events, their results should not be neglected by investors. As we showed convincingly, director election outcomes contain important insights about the directors' ability to monitor and advise management efficiently and subsequent firm performance. Thus, investors should take these results into account when making their investment decisions. Moreover, our results suggest that the director nomination process might be still suboptimal. Shareholders seem to anticipate whether directors contribute to shareholder value and use their votes to address this issue. Therefore, an increase in the use of proxy access might enhance the director-firm matching.

Nonlinear Relationships in Bankruptcy Prediction and Their Effect on the Total Cost of Misclassification: Empirical Evidence on Listed U.S. Companies

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Abstract

This study uses a generalized additive model to identify and analyze nonlinear relationships between accounting-based and market-based independent variables and how these affect bankruptcy predictions. Specifically, it examines which of the independent variables that Altman (1968), Altman (2000) and Campbell et al. (2008) used affect nonlinearly a company's probability of bankruptcy and what specific form these nonlinear relationships take. Drawing on comprehensive data on listed U.S. companies, we show empirically that the bankruptcy prediction is influenced by statistically and economically relevant nonlinear relationships between these variables. Our results indicate that taking into account these nonlinear relationships improves significantly several validity measures. We also introduce a validity measure that is based on the total cost of misclassification and demonstrate that generalized additive models can reduce substantially both the extent of misclassification and the total cost that this entails. Our findings show that it is necessary to take into account nonlinear relationships in order to increase the accuracy of bankruptcy predictions and reduce the total cost of misclassification.

Keywords: accounting-based information, bankruptcy, bankruptcy prediction, cost of misclassification, generalized additive model, listed U.S. companies, market-based information, nonlinear relationships, probability of bankruptcy, validity measure
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2.1 Introduction

The primary aim of research on bankruptcy prediction is to estimate as accurately as possible the probability of a company becoming bankrupt (for an overview see, e.g., Altman and Saunders (1997); Balcaen and Ooghe (2006); Bellovary et al. (2007); Dimitras et al. (1996); Scott (1981)). The accuracy of such forecasts largely depends on the methods and models that are applied and on selecting the most suitable explanatory variables for the purpose of predicting bankruptcy (Laitinen and Kankaanpaa, 1999). In general, the accuracy of bankruptcy predictions increases with the complexity of the empirical methods and models and with the number of explanatory variables that researchers use.

The methodology that analysts apply has become very diversified and includes structural models (Black and Cox (1976); Fabozzi et al. (2010); Merton (1974)), reducing models (Jarrow and Turnbull, 1995), heuristic methods, such as expert systems (Messier Jr and Hansen, 1988), models based on chaos theory (Lindsay and Campbell, 1996), univariate and multivariate discriminant analyses (Altman (1968); Altman Edward et al. (1977); Beaver (1966)), survival analyses (Lane et al. (1986); Luoma and Laitinen (1991); Shumway (2001)), neuronal networks (Charitou et al. (2004); Neves and Vieira (2006)), support vector machines (Min and Lee (2005); Wang et al. (2005)), and, more recently, gradient boosting models (Jones, 2017). For example, Jones (2017) uses 91 explanatory variables on shareholder structure and management compensation, variables that proxy size effects, market-based and accounting-based variables, macro-economic variables, analyst recommendations, and industry variables. However, models that are designed for predicting bankruptcy as accurately as possible but are not sufficiently plausible from an economic perspective are unlikely to be useful in practice (see, e.g., Altman et al. (1994); see also the critical study of neural networks by Hayden and Porath (2011)).

The methods and models used for predicting bankruptcy have improved impressively in recent years with respect to validity measures that are based either on likelihood, such as Nagelkerke's pseudo-R^2 (Nagelkerke et al., 1991) or Akaike's information criterion (Akaike, 1998), or on classification, such as the accuracy ratio (Tasche (2005); Trueck and Rachev (2009), pp. 26–28) or the area under curve (AUC; Engelmann (2006)). However, all such models involve a trade-off between statistical validity and comprehensibility. While more complex empirical models increase the validity of measures based on likelihood or classification, they often tend to be harder to interpret (Jones et al. (2015), Jones (2017)).

An effective bankruptcy prediction model needs to capture the actual effects of the most important explanatory variables on the probability of bankruptcy and still be clear and interpretable. Furthermore, the main criterion for evaluating such a model should be how it affects the total cost of misclassification, rather than on validity measures that are solely based on either likelihood or classification.

Existing models are often hard to comprehend and interpret, because they do not show clearly how the explanatory variables and the probability of bankruptcy interrelate. This is often the case when there are nonlinear relationships between the explanatory variables and the predictor or the non-monotonous effects of the explanatory variables on the probability of bankruptcy. While several studies only assume the existence of such nonlinear relationships (Atiya (2001); Bruderl and Schussler (1990); Saunders and Allen (2010)), some studies have provided empirical evidence that there are indeed such relationships among the independent variables of the models they have used.

Several studies apply univariate methods on categorical independent variables derived from annual financial statements and analyze nonlinear effects with respect to quantiles of classified data (e.g., Altman (2010); Estrella et al. (2000); Falkenstein et al. (2000); Hayden (2011); Serrano-Cinca (1997); Sobehart et al. (2000); Van Gestel et al. (2005)). Multivariate forecast models provide more detailed insights into the nonlinear relationships between the independent variables and the predictor or the non-monotonous effects on the probability of bankruptcy. Some of the studies that apply generalized additive models (GAMs) have, in fact, detected a range of nonlinear relationships with respect to analyses of creditworthiness (Alp et al. (2011); Burkhard and De Giorgi (2006); Lohmann and Ohliger (2018); Djeundje and Crook (2019)) and bankruptcy prediction (Berg (2007); Cheng et al. (2010); Dakovic et al. (2010); Hwang et al. (2007)). However, most of these studies focus on comparing several empirical models from a strictly statistical perspective and do not describe the nonlinear effects they identify in sufficient detail nor interpret them from an economic perspective. One exception is the study by Lohmann and Ohliger (2017), which examines the specific form of nonlinear relationships between accounting-based independent variables and the predictor for the probability of bankruptcy. Using data on limited German companies, the authors show that nonlinear relationships are observed both below and above specific thresholds with respect to a company's equity ratio, asset structure ratio based on tangible assets, return on assets, sales, and age.

One problem that many models for predicting bankruptcy share is that neither validity measures based on likelihood nor those based on classification take into account the economically relevant costs of misclassification. If the type of misclassifications has an impact on those costs, these commonly used validity measures may lead to inaccurate conclusions about the economic benefits of a particular empirical model. More specifically, the costs that result from misclassifying companies that are, in fact, bankrupt, are likely to be higher than the costs that result from misclassifying companies that are, in fact, solvent (Takahashi et al. (1984); Trueck and Rachev (2009);Wilson and Sharda (1994); Yang et al. (1999)). Consequently, in economic terms, an empirical model that is statistically more valid may be less desirable than an alternative of lower statistical validity. Overall, traditional validity measures perform inconsistently because they do not take into account the economically relevant costs of misclassification. To construct an informative and economically relevant validity measure, it is necessary to take into account the economically relevant costs of misclassification.

The present study uses data on listed U.S. companies covering the period 2000–2017 to examine whether taking into account nonlinear relationships in GAMs improves the accuracy with which generalized linear models (GLMs) predict bankruptcy and, if so, to what extent. Our study contributes to research on predicting bankruptcy in three ways: first, we re-estimate the bankruptcy prediction models that Altman (1968), Altman (2000)) and Campbell et al. (2008) used. We compare their models to derive empirical evidence on the extent to which the effects of the independent variables on the probability of bankruptcy change over time. Second, we apply GAMs to identify nonlinear relationships between relevant variables. We explain that the estimated spline functions can be analyzed and interpreted with respect to every independent variable and its effect on the probability of bankruptcy. This provides substantial insights into cause-effect relationships. The comparison between the estimated spline functions and the estimated linear functions reveals in which of the independent variables' value ranges the estimated linear functions underestimate or overestimate the actual (nonlinear) effects. Third, we show that, compared to GLMs, GAMs increase the validity of measures based on either likelihood or classification. We examine in depth the advantages of using GAMs by introducing a validity measure that is based on the total cost of misclassification and therefore reflects the economic consequences of misclassification. The comparison between GAMs and GLMs shows that the total cost of misclassification can be reduced by up to 18.9%.

The paper is structured as follows: in the next section we will describe our methodology: we will explain how we apply GLMs and GAMs and derive a validity measure based on the total cost of misclassification. In the third section we will present our empirical data, the dependent and independent variables we used, and the relevant descriptive statistics and correlations. In the fourth section we will present the results we derived from the estimated bankruptcy prediction models: we will analyze the nonlinear effects between the independent variables and the predictor for the probability of bankruptcy and we will determine the validity of measures based on the total cost of misclassification. Finally, in the last section we will summarize the main results and discuss their practical implications.

2.2 Methodology

2.2.1 Generalized Linear Models and Generalized Additive Models

Predicting bankruptcy requires that a company's solvency status is coded in a binary manner ($solvency = 0$; $bankruptcy = 1$). Following this approach, we transformed the information on qualitative bankruptcy that we drew from our data into a Bernoulli-distributed measure. This metric measure, which we subsequently used in regression analysis, can be interpreted as the metric probability π_i of company i being in the class *bankruptcy*. In GLMs, the probability π_i depends on a set of p independent variables with the values $x_{i1}, x_{i2}, ..., x_{ip}$ and on the applied response function $h(\cdot)$, which transforms the results of the linear function with the coefficients $\beta_0, \beta_1, ..., \beta_p$ (Nelder and Wedderburn, 1972). In equation (1) we calculate the probability π_i of company i being in the class *bankruptcy* on the basis of a GLM.

$$\pi_i = F(\eta_i) = \left(\beta_0 + \sum_{j=1}^{p} \beta_j \cdot x_{ij}\right) \tag{1}$$

In a GLM with a binary dependent variable, the response function $h(\cdot)$ has to be a distribution function $F(\cdot)$ (Maddala (1986); Rauhmeier (2006)). For example, in a probit GLM the distribution function of the standard normal distribution is applied, while in a logit GLM the distribution function of the logistic distribution is applied. The variance of the logistic distribution is greater than the variance of the standard normal distribution (Amemiya (1981); Fahrmeir and Tutz (2013)). However, the choice of distribution functions should not influence significantly the results (Porath, 2006). Due to the slope of the distribution function, the probability $\pi_i = F(\eta_i)$ retains the constraint $\pi_i \in [0, 1]$. The predictor eta_i is still a linear function, but the relationship between each independent variable and the probability π_i is no longer linear, because of the link with the distribution function $F(\cdot)$. However, as every distribution function is strictly non-decreasing (Jacod and Protter, 2012), each independent variable has a monotonic effect on the probability π_i (Hosmer Jr et al., 2013).

The GLM assumes that there is a linear relationship between each independent variable and the predictor η_i. This assumption is often too restrictive, as the marginal effect of an independent variable on the predictor is often not constant, but depends on the value this variable takes. It is possible to introduce into a GLM nonlinear relationships by means of mathematical transformations and to model any non-monotonous effects by means of a piece wise linear function. Nevertheless, to achieve an accurate estimation, it is necessary to have detailed information about the slope of the functional relationship between the independent and the dependent variable.

It is worth noting that the functional form of existing nonlinear relationships is usually unknown, so it is only by chance that a GLM can provide an accurate prediction of a company's probability of bankruptcy. Considering that several studies assume the existence of such nonlinear relationships (Atiya (2001); Erlenmaier (2006); Saunders and Allen (2010)), using a GLM can prove a serious problem with respect to the validity of the bankruptcy prediction. This problem can be avoided by integrating a more general form of the predictor, according to Equation 2. Replacing the linear predictor η_i with the additive predictor η_i^{add} renders the form of the predictor more flexible. This, in turn, makes it possible to examine a nonlinear relation between an independent variable and η_i^{add}.

$$\pi_i = F(\eta_i^{add}) = \left(\beta_0 + \sum_{j=1}^{p} \beta_j \cdot x_{ij}\right) \tag{2}$$

The functions $f_1(\cdot), f_2(\cdot), ..., f_p(\cdot)$ follow an unspecified form. If, however, these functions followed a specific linear form, the GAM would be transformed into a GLM. This explains why the GLM is regarded as a special case of a GAM.

The first intuitive approach to modeling an unspecified function $f(\cdot)$ in a GAM involves using a polynomial model of rank g. Although this simple approach enables us to examine nonlinear relationships, rank g often needs to be high in order to obtain a good fit to the data (Everett and Watson (1998); Hastie and Tibshirani (1995)). Consequently, applying polynomial splines might be preferable. In polynomial splines the range of the independent variables is split at intervals whose limits are designated as knots k_n, with $n = 1, ..., m$. The lower limit of the range $[x_{min}, x_{max}]$ is k_1 and the upper limit of the range $[x_{min}, x_{max}]$ is k_m. For every interval, a polynomial of rank g is estimated. This produces a better fit to the data than a polynomial model without the split would. Furthermore, the unspecified function $f(\cdot)$, which is characterized by a number of polynomial splines, has to be $g-1$-times continuous differentiable. This requirement renders the function smooth. The differentiability prevents jump discontinuity at the interval limits (Kneib, 2006).

We can use the base functions that relate to either the truncated power series (Hastie and Tibshirani, 1990) or to the B-spline-base (Kneib, 2006). to model the splines. Both approaches involve two subjective design elements: choosing the number m and the position of the knots is subjective, although knots are usually arrayed equidistantly or on the basis of the quantiles. Using penalized splines helps avoid these problems. This method involves using a polynomial spline with a large number of knots to approximate function $f(\cdot)$. The large number of knots lends flexibility to this approximation and how the knots are arrayed matters less.

To achieve balance between flexibility and smoothing, an additional penalty term is established for every spline function in the maximum likelihood estimation of the GAM. This term penalizes highly different interval-specific polynomials. With regard to likelihood maximization, the penalty term is weighted with a smoothing parameter λ, so the variability of a penalized spline is controlled by a single parameter λ (Eilers and Marx, 1996). Higher values of λ decrease the variability of function $f(\cdot)$ and increase the smoothness of function $f(\cdot)$. However, it is not possible to increase both smoothness and adaption to the data simultaneously. It is therefore necessary to use the generalized cross-validation criterion in order to objectify the smoothing parameter λ (Eilers and Marx (1996); Green (1994)). Consequently, in order to determine the smoothing parameters, the generalized cross-validation criterion has to be minimized.

2.2.2 The Total Cost of Misclassification as a Validity Measure

The validity measure for the bankruptcy prediction models that we introduce and apply here is based on the total cost of misclassification. In contrast to validity measures that are based either on likelihood or on classification, this validity measure captures the actual economic effects of a bankruptcy prediction model. The effect of different misclassification errors which are associated with different cost of misclassification on the validity measure AUC was analyzed by Hand (2005) and Hand (2006) and led to the development of the H measure as an alternative validity measure (Hand, 2005). However, the H measure and AUC show comparable relative validity measures of various prediction models in the credit scoring context (Jones et al. (2015), Jones (2017)). In contrast to the H measure, we take into account the costs that are associated with both types of misclassification. As a result, we are able to evaluate a bankruptcy prediction model by examining the extent to which it reduces the total cost of misclassification in comparison to the alternative bankruptcy prediction model.

The total cost of misclassification depends on three main factors: first, the number of misclassified but actually solvent companies h_{01}; second, the number of misclassified but actually bankrupt companies h_{10}; third, the costs that are associated with both types of misclassification. Misclassification has certain economic consequences. When bankrupt companies are misclassified as solvent, these consequences consist in the total or partial default of the outstanding interest and repayments associated with the financial engagement. When solvent companies are misclassified as bankrupt, these consequences consist in the foregone profits and other opportunity costs that are associated with the potential financial engagement. Overall, the cost $C(1)$ that arises from the misclassification of actually bankrupt companies tends to exceed the cost $C(0)$ that arises from the misclassification of actually solvent companies (Takahashi et al. (1984); Trueck and Rachev (2009); Wilson and Sharda (1994); Yang et al. (1999)).

The objective of a bankruptcy prediction model is not to minimize the absolute number of misclassified companies, but to identify and implement a decision rule that minimizes the total cost of misclassification. The a posteriori probabilities are weighted with the corresponding costs $C(0)$ and $C(1)$. A single company is classified as bankrupt ($\hat{y}_i = 1$) if the a posteriori probability of bankruptcy, when weighted with cost $C(1)$, does not drop below the a posteriori probability of solvency, when weighted with cost $C(0)$. Equation (3) expresses this decision rule formally.

$$\hat{y}_i = \begin{cases} 1 & if \;\; C(1) \cdot P(1 \mid x_i) \geq C(0) \cdot P(0 \mid x_1) \\ 0 & if \;\; C(1) \cdot P(1 \mid x_i) < C(0) \cdot P(0 \mid x_1) \end{cases} \tag{3}$$

According to Equation (3), a company is classified as bankrupt if Equation (4) holds.

$$P(1 \mid x_i) \geq \frac{C(0)}{C(0) + C(1)} \tag{4}$$

The decision rule that minimizes the total cost of misclassification is determined entirely by the relative costs $C(0)$ and $C(1)$. The absolute cost values are irrelevant. Equation (4) shows that if $C(0)$ coincides with C(1), a company has to be classified as bankrupt above the 50% threshold probability of bankruptcy. However, in most cases $C(1)$ is likely to exceed $C(0)$, which means that the threshold probability of bankruptcy is below 50% (Laitinen and Kankaanpaa, 1999).

In the next step, we determine the threshold probability of bankruptcy that minimizes the total cost of misclassification relating to all companies of a specific sample. The total cost of misclassification K is given by Equation (5).

$$K = h_{01} \cdot C(0) + h_{10} \cdot C(1) \tag{5}$$

We modify Equation (5) by introducing $1 - Specificity$ and $Sensitivity$, which are elements of the receiver operating characteristic (ROC) curve (Engelmann 2011). The first of these, $1 - Specificity$, corresponds to the proportion of misclassified but actually solvent companies $h_{01}/h_{0\bullet}$, where $h_{0\bullet}$ denotes the absolute total number of all companies that were actually solvent. The second element, $Sensitivity$, derives from $1 - h_{10}/h_{1\bullet}$ and corresponds to the proportion of bankrupt companies that have been properly classified, where $h_{1\bullet}$ denotes the absolute total number of all companies that were actually bankrupt. According to Equation (6), the total cost of misclassification depends on $1 - Specificity$ and $Sensitivity$.

$$\begin{aligned} K &= \frac{h_{01}}{h_{0\bullet}} \cdot h_{0\bullet} \cdot C(0) + \frac{h_{10}}{h_{1\bullet}} \cdot h_{1\bullet} \cdot C(1) \\ &= (1 - Specificity) \cdot h_{0\bullet} \cdot C(0) + (1 - Sensitivity) \cdot h_{1\bullet} \cdot C(1) \end{aligned} \tag{6}$$

Deriving Equation (6) with respect to $1 - Specificity$ minimizes the total cost of misclassification.

$$\frac{\partial K}{\partial(1 - Specificity)} K = h_{0\bullet} \cdot C(0) - \frac{\partial Sensitivity}{\partial(1 - Specificity)} h_{1\bullet} \cdot C(1) = 0 \tag{7}$$

When Equation (6) holds, the total cost of misclassification is minimized.

$$\frac{\partial Sensitivity}{\partial(1 - Specificity)} K = \frac{h_{0\bullet \cdot C(0)}}{h_{1\bullet \cdot C(1)}} \tag{8}$$

The minimum of the total cost of misclassification is reached at the point where the slope of the ROC curve is given by $\frac{h_{0\bullet \cdot C(0)}}{h_{1\bullet \cdot C(1)}}$. This allows us to determine the $Sensitivity$, $1 - Specificity$, and threshold probability of bankruptcy that minimize the total cost of misclassification. As a result, we can compare the total cost of misclassification that is associated with the estimated bankruptcy prediction models. For that purpose, we have to calculate separately the cost-minimizing threshold probability of bankruptcy for each estimated bankruptcy prediction model and for each cost relation $C(0)/C(1)$.

2.3 Empirical Data

2.3.1 Sample Refinement

Our empirical analysis is based on data we collected on 8,557 listed U.S. companies for the fiscal years from 2000 to 2017. The information on a company's bankruptcy was taken from the UCLA-LoPucki Bankruptcy Research Database and from the bankruptcy database that was built and is maintained by Sudheer Chava (Chava (2014); Chava et al. (2011)). The information on bankruptcy that our data provide shows whether a company filed for bankruptcy under Chapter

7 or Chapter 11 before the end of 2017 and, for companies that did, when. The independent variables were extracted from the Compustat database and the CRSP database and correspond to the accounting-based and market-based independent variables that Altman (1968, 2000) and Campbell et al. (2008) applied. We did not take into account further accounting-based and market-based independent variables (e.g., Ohlson (1980)), as financial ratios that relate to the same area are often correlated to a substantial extent (Beaver et al., 2005). We also collected information on each company's industry. We excluded all companies in the category "Money & Finance" of the Fama-French 12-industry classification scheme. Overall, we gathered empirical raw data that comprise 143,878 annual observations on 16,942 listed U.S. companies. In addition to data on each company's solvency status, each annual observation includes the annual financial statement and corresponding market data. We processed these data in five steps that we outline in Table 2.1 and extracted a refined sample on which we based our empirical analyses.

Table 2.1: The five-step procedure of processing the raw data (bankruptcies in brackets).

		Observations	Companies
	Collected detailed data on listed U.S. companies for the fiscal years 2000-2017, derived from the COMPUSTAT and CRSP databases	143.878	16.942
(1)	Processed the collected data to derive a bankruptcy prediction for a triennial period after the reporting date 2000–2014	127.34	16.594
		-2.653	-1.114
(2)	Eliminated missing variables	80.16	10.156
		-2.377	-1.029
(3)	Eliminated implausible variables	79.69	10.15
		-2.372	-1.027
(4)	Eliminated outliers	52.874	8.557
		-1.277	-765
(5)	Compiled each company's profile on the basis of the most recent available observation	8.557	8.557
		-765	-765

The empirical model predicts a company's probability of bankruptcy within a triennial period. A company that filed for bankruptcy under Chapter 7 or Chapter 11 within three years after the reporting date was classified as "bankrupt." This means that it was not possible to predict whether a company would remain solvent in the three years following any date during the period spanning the fiscal years 2015–2017. Consequently, having collected our data, in the first step we had to exclude all annual observations after the fiscal year 2015 and reduce the empirical database to 127,340 annual observations drawn from 16,594 listed U.S. companies.

In the second and third steps we chose our metric independent variables, drawing on Altman (1968, 2000) (five independent variables) and Campbell et al. (2008) (nine independent variables). We describe these variables in detail in the next section. Any annual observations that lacked the data relating to these variables or where one or more independent variables had an implausible sign were eliminated. These refinements reduced our sample by 47,650 annual observations.

In the fourth step, we identified outliers and eliminated the respective observations in order to avoid distorted estimations. Cases where the value of a company's independent variable is below the 2.5% quantile or above the 97.5% quantile were classified as outliers. Every annual observation that produced at least one outlier was eliminated from our analysis (Dakovic et al., 2010). As a result of this procedure, the usable data were further reduced to 52,874 annual observations derived from 8,557 listed U.S. companies.

Finally, we had to decide whether we should use each company's most recent available observation or time-coherent panel data. To avoid dependencies between single observations, we decided to apply the first method. This reduced our sample to 8,557 annual observations that correspond to 8,557 listed U.S. companies. The method we chose ensures that our annual observations are reliable. If we had used panel data, we would have had to apply generalized linear mixed models and generalized additive mixed models. As a result of this approach, however, our GLMs and GAMs would have become even more complex.

2.3.2 Dependent und Independent Variables

The dependent variable reflects the type of bankruptcy. We classified each bankrupt company according to the type of failure (Dickerson & Kawaja, 1967; Erlenmaier, 2011; Schwarz & Arminger, 2010) and to the period within which it became bankrupt. A company was classified as "bankrupt" if it had declared bankruptcy under Chapter 7 or Chapter 11 within three years after the annual financial statement that we consulted (for a similar approach, see Dakovic et al., 2010).

Our final sample comprises 765 bankruptcies. The relatively high a priori bankruptcy rate of about 8.9% results from the forecast horizon, which includes the economic slowdown after the dotcom bubble in 2000 and the financial crisis that began around 2007. A second factor that explains the relatively high a priori bankruptcy rate is that we chose a three-year forecast period.

Table 2.2: Financial ratios used in Altman (1968, 2000).

Book value of equity	$BVE =$ $Stockholder\ equity + Deferred\ taxed + Investment\ tax\ credit - Preferred\ stock$
Share of liquid assets in total assets	$WC\_TA = \frac{Working\ Capital}{Total\ assets}$
Profitability (reflects the company's age and earning power)	$RE\_TA = \frac{Retained\ earnings}{Total\ assets}$
Operating efficiency (excepting tax and leveraging factors)	$EBIT\_TA = \frac{Earnings\ before\ interest\ and\ taxes}{Total\ assets}$
Accounting-based financial position of the company	$BVE\_TL = \frac{BVE}{Total\ liabilities}$
Total asset turnover	$SA\_TA = \frac{Sales}{Total\ assets}$

The independent variables consist of metric variables derived from the annual financial statements and stock-market information of the listed U.S. companies. In particular, the bankruptcy prediction models we estimate are based on the independent variables that either Altman (1968, 2000) or Campbell et al. (2008) used. In Altman's work (Altman (1968, 2000)), the independent variables consist of the five financial ratios presented in Table 2.2. We applied a set of independent variables where every variable result was derived entirely from accounting information. To that end, instead of a company's market-based financial position (Altman, 1968), we used its accounting-based financial position (Altman, 2000). Furthermore, we also decided to use the market-based independent variables Campbell et al. (2008) describe. These represent two sets of independent variables (see Table 2.3) that differ in the valuation of the total assets (i.e., adjusted total assets vs. market-valued total assets). We also take into account the year of each observation and each company's industry, according to the Fama-French 12-industry classification scheme. In our context, categorical variables are only of secondary importance, because they are not useful in the analysis of nonlinear relationships. Nevertheless, we included them to make our database as comprehensive as possible.

Table 2.3: Financial ratios used in Campbell et al. (2008).

Adjusted total assets	$ATA = Total\ assets + 0.1 \cdot (MVE - BVE)$
Market value of equity	$Price\ close\ annual\ calendar\ \cdot$ $Common\ shares\ outstanding$
Market-valued total assets	$MTA =$ $Market\ value\ of\ equity + Total\ liabilities$
Adjusted profitability ratio	$NI\_ATA = \frac{Net\ income}{ATA}$
Market-based profitability ratio	$NI\_MTA = \frac{Net\ income}{MTA}$
Adjusted leverage of the company	$TL\_ATA = \frac{Totalliabilities}{ATA}$
Market-based leverage of the company	$TL\_MTA = \frac{Totalliabilities}{MTA}$
Share of liquid assets in the market-valued total assets	$CA\_MTA = \frac{Cash+Short\ termassets}{MTA}$
Market-to-book ratio	$MB = \frac{Market\ value\ of\ equity}{BVE+0.1\cdot(MVE-BVE)}$
Annualized 50-trading-days log excess return on each firm's equity relative to the S&P 500 Index	$EXC\ RET = log(1+R_{i,t} - log(1+R_{S\&P500_t})$
Annualized standard deviation of each firm's daily stock return over the past 50 days	$SIGMA_{i,t-1,t-2,t-3} =$ $\left(252 \cdot \frac{1}{N-1} \cdot \sum_{k\in\{t-1,t-2,t-3\}} r_{i,k}^2\right)$
Relative company size, based on each firm's market valuation (measured as the log ratio of its market capitalization to that in the S&P 500 Index)	$RSIZE =$ $log\left(\frac{Market\ value\ of\ equity}{Total\ market\ valuation\ of\ S\&P500}\right)$
Price per share, measured as the log and truncated above at \$15	$PRICE = log\left(min\{15 \mid price\ per\ share\}\right)$

2.3.3 Descriptive Statistics and Correlations

The descriptive statistics of the independent variables are displayed in Table 2.4 and show the expected characteristics. Our analysis reveals statistically significant differences (p-value < 0.01) between solvent and bankrupt companies in the mean and median values with respect to almost all metric independent variables. The difference in the mean of the independent variable RE_TA is only statistically significant at a low level (p-value < 0.05). In contrast to that, the difference in variance is not statistically significant for the independent variables WC_TA. RE_TA, S_TA, and MB.

Table 2.4: Descriptive statistics of the independent variables.

	Min.			Mean			Median			Max.			SD		
Sample	Bank.	Non-B.	All	Bank.	Non-B.	All	Bank.	Non-B.	All	Bank.	Non-B.	All	Bank.	Non-B.	All
Number	765	7.792	8.557	765	7.792	8.557	765	7.792	8.557	765	7.792	8.557	765	7.792	8.557
WC_TA	–0.715	–0.714	–0.715	0.136	0.244	0.236	0.108	0.212	0.201	0.830	0.832	0.832	0.257	0.259	0.260
RE_TA	–20.50	–22.60	–22.60	–1.137	–0.885	–0.904	–0.254	0.027	-0.046	0.686	0.701	0.701	2,705	2,567	2,578
EBIT_TA	–1.370	–1.520	–1.520	–0.139	–0.041	–0.049	–0.044	0.041	0.035	0.253	0.262	0.262	0.268	0.249	0.252
BVE_TL	–0.430	–0.428	–0.430	1,169	1,919	1,862	0.539	1,125	1,065	13-Apr	14.95	14.95	1,875	2,219	2,204
S_TA	0.000	0.000	0.000	0.977	0.934	0.937	0.807	0.785	0.787	3,318	3,319	3,319	0.788	0.693	0.701
NI_ATA	–1.230	–1.300	–1.300	–0.186	–0.072	–0.081	–0.107	0.011	0.006	0.172	0.180	0.180	0.241	0.215	0.219
NI_MTA	–0.718	–0.726	–0.726	–0.133	–0.045	–0.051	–0.089	0.008	0.005	0.118	0.120	0.120	0.161	0.133	0.137
TL_ATA	0.059	0.054	0.054	0.642	0.467	0.480	0.674	0.451	0.466	1,376	1,458	1,458	0.267	0.244	0.250
TL_MTA	0.019	0.018	0.018	0.578	0.359	0.376	0.662	0.317	0.332	0.925	0.926	0.926	0.274	0.238	0.248
CA_MTA	0.001	0.001	0.001	0.087	0.123	0.120	0.043	0.079	0.076	0.656	0.664	0.664	0.113	0.130	0.130
MB	–3.740	–4.020	–4.020	1,908	2,745	2,681	1,063	1,906	1,845	15.89	16.30	16.30	2,678	2,768	2,770
EXC_RET	–3.380	–3.390	–3.390	–0.700	–0.105	–0.151	–0.631	–0.036	–0.062	2,135	2,237	2,237	1,218	0.931	0.969
SIGMA	0.164	0.135	0.135	0.885	0.590	0.612	0.810	0.474	0.496	2,336	2,370	2,370	0.414	0.389	0.399
RSIZE	–15.50	–15.60	–15.60	–11.72	–10.73	–10.80	–11.76	–10.74	–10.85	–5.887	–5.868	–5.868	1,643	2,157	2,138
PRICE	–1.560	–1.560	–1.560	1,140	1,811	1,760	1,141	2,281	2,175	2,708	2,708	2,708	1,018	1,083	1,092

Most independent variables in our three sets (Altman (1968); Altman (2000); Campbell et al. (2008) – ATA; Campbell et al. (2008) – MTA) are moderately or little correlated (see Table 2.5). The correlation between RE_TA and $EBIT\_A$ is high, as both independent variables relate to a company's earnings. Furthermore, $PRICE$ exhibits high correlations to NI_MTA, EXC_RE, $SIGMA$, and $RSIZE$. We tested each set of independent variables for multicollinearity between each metric independent variable and all other independent variables. The variance inflation factor shows that there is no multicollinearity, apart from the identified correlations within the three sets of independent variables. The contingency analysis does not reveal any strong relationships between the metric and categorical independent variables, so we are not restricted in our use of multivariate models. Consequently, the three sets of independent variables demonstrate the expected data structures and serve as a valid database.

Table 2.5: Correlations of the independent variables.

Altman (1968, 2000)	WC_TA	RE_TA	$EBIT\_TA$	BVE_TL	S_TA
WC_TA	1,000				
RE_TA	–0.131	1,000			
$EBIT\_TA$	–0.194	0.616	1,000		
BVE_TL	0.480	–0.064	–0.150	1,000	
S_TA	–0.042	0.121	0.260	–0.227	1,000
Campbell et al. (2008) – ATA	NI_ATA	TL_ATA	EXC_RET	$SIGMA$	$RSIZE$
NI_ATA	1,000				
TL_ATA	0.009	1,000			
EXC_RET	0.197	–0.025	1,000		
$SIGMA$	–0.385	0.065	–0.185	1,000	
Campbell et al. (2008) – MTA	NI_MTA	TL_MTA	CA_MTA	MB	EXC_RET
$RSIZE$	0.407	–0.102	0.165	–0.520	1,000
NI_MTA	1,000				
TL_MTA	-0.080	1,000			
CA_MTA	–0.259	–0.258	1,000		
EXC_RET	0.213	–0.049	–0.048	0.021	1,000
MB	0.032	–0.424	–0.102	1,000	
$SIGMA$	–0.416	0.146	0.092	–0.048	–0.185
$RSIZE$	0.446	–0.182	–0.220	0.196	0.165
$PRICE$	0.559	–0.228	–0.208	0.159	0.314
	$SIGMA$	$RSIZE$	$PRICE$		
$SIGMA$	1,000				
$RSIZE$	–0.520	1,000			
$PRICE$	–0.583	0.718	1,000		

2.4 Results

2.4.1 Estimated Bankruptcy Prediction Models

To analyze the relationships between the independent variables and the dependent variable, we estimated both GLMs and nonlinear GAMs with respect to the three sets of independent variables Altman (1968, 2000) and Campbell et al. (2008) used. The estimation models should exhibit sufficient external validity and be usable with existing and new data from the same population. Furthermore, the accuracy of the predictions that the models allow us to make should be sufficiently high. Taking into account nonlinear effects increases the complexity of the models and this might impair their external validity. To ascertain their validity, we randomly split our sample of 8,557 observations into a training sample (5,705) and a validation sample (2,852). Both sub samples originated from the same population and are independent of each other. We ran means comparison tests and chi-square homogeneity tests, but did not find any structural and statistically significant differences between the sub samples, so the results of the correlation analysis also apply to these sub samples.

In the three GLM and three GAM estimations, we included the independent variables Altman (1968, 2000) used, the adjusted independent variables (ATA) Campbell et al. (2008) used, and the market-based independent variables (MTA) used in Campbell et al. (2008). In the GAMs, we applied penalized splines to model the nonlinear effects of the independent variables. We put the GAMs in concrete terms by using basic functions of rank $g = 3$ and 12 equidistant intervals for each penalized spline. The smoothing parameter is determined by the generalized cross-validation criterion. The year of the observation and the company's industry, according to the Fama-French 12-industry classification, are also taken into account as categorical independent variables. The categorical independent variables are treated as dummy variables.

The estimations of the GLMs and the GAMs are presented in Table 2.6. Although the GLMs and GAMs are estimated with an intercept and dummy variables for the year of the observation and the industry, Table 2.6 only reports the results with regard to the metric independent variables. The results from the GLMs include the regression coefficients. The asterisks denote the level of significance based on the likelihood ratio test (Wood, 2017). The results of the metric independent variables in the GAMs show the equivalent degrees of freedom df_f, which represent the variability of the estimated splines of the metric independent variables. The value $df_f = 1$ shows that the estimated spline corresponds to a linear function and the increasing degrees of freedom indicate the level of increases in nonlinearity. Again, the asterisks denote the level of significance based on the likelihood ratio test (Wood, 2017).

Table 2.6: Model estimations and validity measures. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05

	Altman		Campbell – ATA		Campbell – MTA	
	GLM1	GAM1	GLM2	GAM2	GLM3	GAM3
WC_TA	–0.558*	2.339				
RE_TA	0.003	7.743*				
$EBIT\_TA$	–1.592***	4.446***				
BVE_TL	–0.252***	4.224***				
S_TA	–0.156	1.001				
NI_ATA			–1.281***	3.488***		
NI_MTA					–2.571***	2.659***
TL_ATA			2.321***	3.762***		
TL_MTA					2.930***	4.122***
CA_MTA					–1.334*	6.043***
MB					0.029	1.003
EXC_RET			–0.399***	3.647***	–0.402***	3.578***
$SIGMA$			0.545***	3.600***	0.585***	3.637***
$RSIZE$			0.031	2.701***	0.122**	2.699***
$PRICE$					–0.004	2.174*
Nagelkerke pseudo-R^2	0.204	0.273	0.270	0.340	0.292	0.364
AIC	2,659.25	2,506.45	2,484.66	2,316.64	2,431.00	2,266.01
AUC training sample	0.806	0.845	0.847	0.877	0.855	0.886
AUC validation sample	0.789	0.822	0.822	0.851	0.834	0.861

The estimated coefficients of the GLMs are comparable to those Altman (1968, 2000) and Campbell et al. (2008) report and largely exhibit the expected signs. With regard to the independent variables Altman (1968, 2000) used, the decreasing values of WC_TA, $EBIT\_TA$, and BVE_TL have a positive and statistically significant effect on the probability of bankruptcy. The GLM estimation of the adjusted independent variables (ATA) that Campbell et al. (2008) used shows that the decreasing values of NI_ATA and EXC_RET and increasing values of TL_ATA and SIGMA significantly increase the probability of bankruptcy. Taking into account the market-based independent variables (MTA) that Campbell et al. (2008) used, we find that the decreasing values of NI_MTA, CA_MTA, and EXC_RET and the increasing values of TL_MTA, $SIGMA$, and $RSIZE$ significantly increase the probability of bankruptcy. However, it should be noted that excluding the independent variable PRICE, which is highly correlated to NI_MTA, EXC_RET, and $SIGMA$, does not change the estimation results.

The GLM estimations correspond to the GAM estimations with respect to the level of significance of the metric independent variables. The equivalent degrees of freedom of the GAM estimations ($df_f > 1.00$) reveal that there are nonlinear relationships between the independent variables and the predictor. Consequently, in order to describe the nonlinear effects' direction, we have to analyze the spline patterns in detail.

2.4.2 Nonlinear Relationships

The equivalent degrees of freedom of the GAM estimations, and thus the estimated nonlinear relationships, differ with regard to the metric independent variables. Figures 2.1 to 2.3 depict the spline patterns of the significant independent variables for the three GAM estimations. The black bold line represents the estimated spline. The value of the independent variable is plotted on the x-axis, while the effect on the predictor is plotted on the y-axis. Higher values on the y-axis indicate a higher probability of bankruptcy. However, because these probabilities also depend on the values of the other variables, we cannot determine them more precisely. The 95% confidence band is shaded gray. To compare the estimated spline patterns with the estimated linear functions, we inserted the linear functions of the GLM estimations and centered the estimated linear functions with the estimated spline patterns at the function value 0. Figures 2.1 to 2.3 also depict the empirical density function of the independent variable as a dotted line, with the maximum value on the right side. The empirical density function matches the descriptive statistics that are presented in Table 2.4. The spline patterns are particularly meaningful within the value range where the empirical density function indicates a large number of observations.

The spline patterns in Figure 2.1 depict the relationships between the independent variables RE_TA, $EBIT\_TA$, and BVE_TL and the predictor of GAM1. The linear function of the independent variable RE_TA indicates a positive (but not statistically significant) effect on the predictor. In contrast, for high values of RE_TA, where the empirical density function indicates a large number of observations, the spline function shows a negative effect on the predictor. Because most observations are located near $RE\_TA = 0$, the 95% confidence band is narrow and the spline function is significant. Within the negative value range ($RE\_TA < 0$) the estimation becomes less certain, because there are fewer observations and the 95% confidence band is thus relatively wider. Overall, the estimated spline function shows that the effect of RE_TA on the predictor is low and inconclusive.

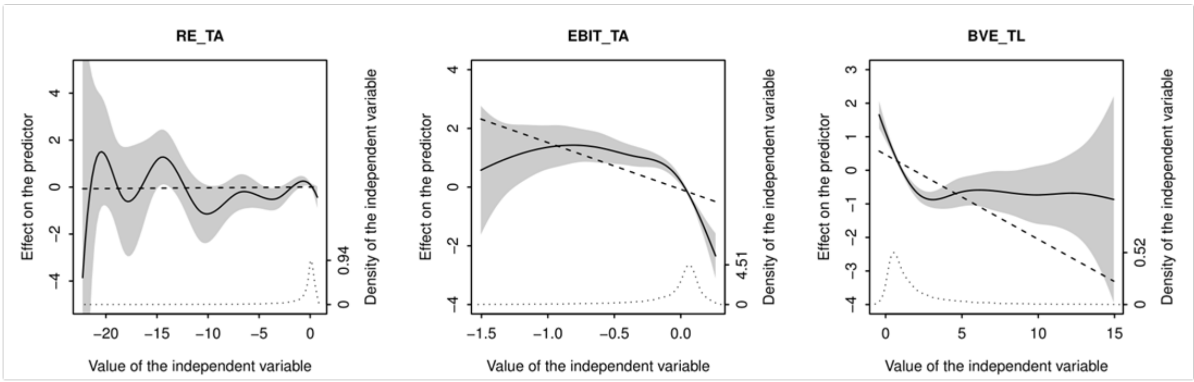

Figure 2.1: Estimated spline patterns of the significant independent variables in GAM1.

From the analysis of the spline function of $EBIT\_TA$ we were able to draw more valid conclusions. For positive values ($EBIT\_TA > 0$), the independent variable $EBIT\_TA$ has a negative and almost linear effect on the predictor. When $EBIT\_TA$ takes negative values, we can assume that the spline pattern for $EBIT\_TA$ is almost constant. If $EBIT\_TA$ deteriorates, this is not likely to have a further effect on the predictor. The estimated linear function overestimates the probability of bankruptcy within the value range $EBIT\_TA >$ and underestimates the probability of bankruptcy when $EBIT\_TA$ takes low negative values ($-0.5 < EBIT\_TA > 0$). As a result, the assumption of a linear relationship will not hold when the company's operations are not profitable and $EBIT\_TA$ takes a low negative value. Furthermore, the estimated linear function indicates that the probability of bankruptcy is overestimated for highly negative values of $EBIT\_TA$. As the number of observations where $EBIT\_TA$ takes highly negative values is low, the 95% confidence band is very wide. It should be noted, however, that the estimated linear function is located within the 95% confidence band for $EBIT\_TA < -0.5$.

The spline pattern of BVE_TL decreases almost linearly the predictor until $BVE\_TL = 2$. That means that the increase in BVE_TL reduces the probability of bankruptcy. For larger values of BVE_TL >2 the estimation becomes less certain, because there are fewer observations and the 95% confidence band is thus relatively wider. The effect of BVE_TL on the predictor decreases in the upper peripheral areas, where we can assume that the spline pattern for $BVE\_TL > 2$ is almost constant. This empirical finding is consistent with the findings of Lohmann and Ohliger (2017) and Van Gestel et al. (2005), who showed empirically that the effect of high equity ratios on the probability of bankruptcy converges towards zero. The decreasing effect of additional potential liability when BVE_TL is already high can explain the nonlinear relationship between BVE_TL and the predictor for the probability of bankruptcy. However, linear functions cannot capture the change in the slope of the spline function, which leads ceteris paribus to either underestimating ($BVE\_TL < 2$) or overestimating ($2 < BVE\_TL < 5$) the probability of bankruptcy.

The spline patterns in Figure 2.2 depict the relationships between the independent variables NI_ATA, TL_ATA, EXC_RET, $SIGMA$, and $RSIZE$ and the predictor of GAM2. The estimated spline function of NI_ATA in Figure 2.2 is comparable to the estimated spline function of $EBIT\_TA$ in Figure 2.1. For slightly negative and positive values ($NI\_ATA > -0.1$), the independent variable NI_ATA has a negative and almost linear effect on the predictor. In contrast to that, highly negative values ($NI\_ATA < -0.1$) do not increase the predictor or, as a result, the probability of bankruptcy. The estimated linear function shows that the probability of bankruptcy is underestimated for low negative values ($-0.5 < NI\_ATA < 0$) and overestimated for positive values ($NI\_ATA > 0$). When NI_ATA takes values around zero, the linear function underestimates the sensitivity of the effect that NI_ATA has on the probability of bankruptcy.

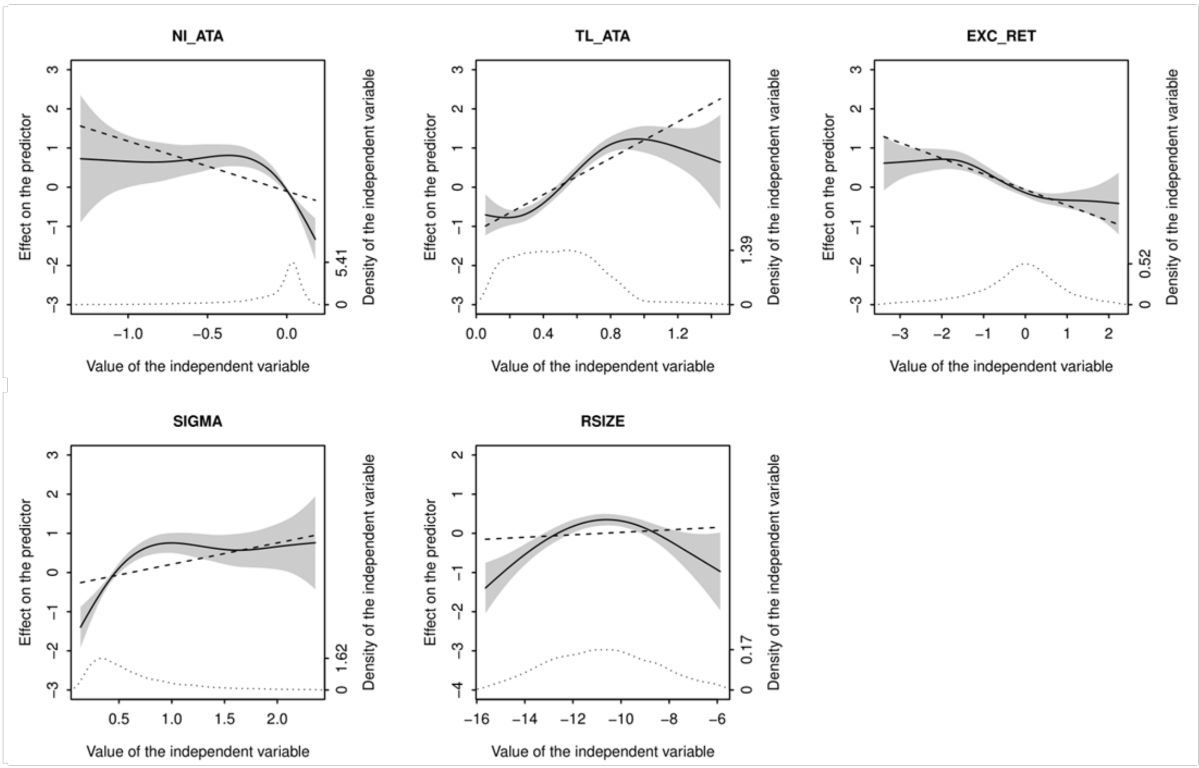

Figure 2.2: Estimated spline patterns of the significant independent variables in GAM2.

The estimated spline function of TL_ATA increases almost linearly within the range $0.4 < TL\_ATA < 1.0$ and thus increases the probability of bankruptcy. The 95% confidence band is narrow within that range. In the peripheral areas the estimation becomes less certain, because there are fewer observations and the 95% confidence band is thus relatively wider. The effect of TL_ATA on the probability of bankruptcy decreases in the lower and upper peripheral areas, where we can assume that the spline patterns for $TL\_ATA < 0.4$ and $TL\_ATA > 1.0$

are almost constant. Consequently, the results we derive from the estimated spline function are consistent with previous empirical evidence that the probability of bankruptcy exhibits low sensitivity when equity ratios are either low (Lohmann and Ohliger (2017); Van Gestel et al. (2005)) or high (Lennox (1999); Lohmann and Ohliger (2017)).

The spline pattern of EXC_RET is comparable to the spline pattern of TL_ATA, as the effect of EXC_RET on the probability of bankruptcy decreases in the lower and upper peripheral areas, where we can assume that the spline patterns for $XC\_RET < -2.0$ and $EXC\_RET > 1.0$ are almost constant. Within the value range $-2.0 < EXC\_RET < 1.0$, increasing values of EXC_RET decrease the predictor of the probability of bankruptcy. The estimated linear function slopes more steeply in the peripheral areas, which indicates a larger effect on the probability of bankruptcy. However, the estimated linear function is within the 95% confidence band, which suggests that the probability of bankruptcy is not significantly overestimated or underestimated.

The estimated spline function of SIGMA slopes upwards almost linearly until the threshold $SIGMA = 1.0$. However, the threshold of $SIGMA = 1.0$, where the positive slope of the splines turns to zero and the splines phase out sideways, indicates the presence of a nonlinear relationship. The comparison between the GLM and the GAM estimations shows that there are relevant overestimations and underestimations within the value range $0.0 < SIGMA < 1.3$.

The spline pattern of $RSIZE$ indicates a reversed U-shaped relationship between $RSIZE$ and the predictor. While the estimated linear function is not statistically significant, the estimated spline function is highly significant. Companies with a relatively low or a relatively high market valuation exhibit a lower probability of bankruptcy. Among these, companies with a relatively low market valuation are likely to be young and still in their "honeymoon" period (Altman (2000); Everett and Watson (1998); Honjo (2000); Hudson (1987)).

The spline patterns in Figure 2.3 depict the relationships between the independent variables NI_MTA, TL_MTA, CA_MTA, EXC_RET, $SIGMA$, $PRICE$, and $RSIZE$ and the predictor in GAM3. The nonlinear relationships in GAM3 are comparable to those in GAM2. The independent variables NI_MTA and TL_MTA exhibit linear relationships for a wider value range. However, we can again observe lower and upper thresholds where the slope of the spline function, and therefore the effect of the independent variable on the predictor, change. As a result, an estimated linear function will usually be inaccurate, because it partly underestimates or overestimates the effect of the independent variable on the predictor.

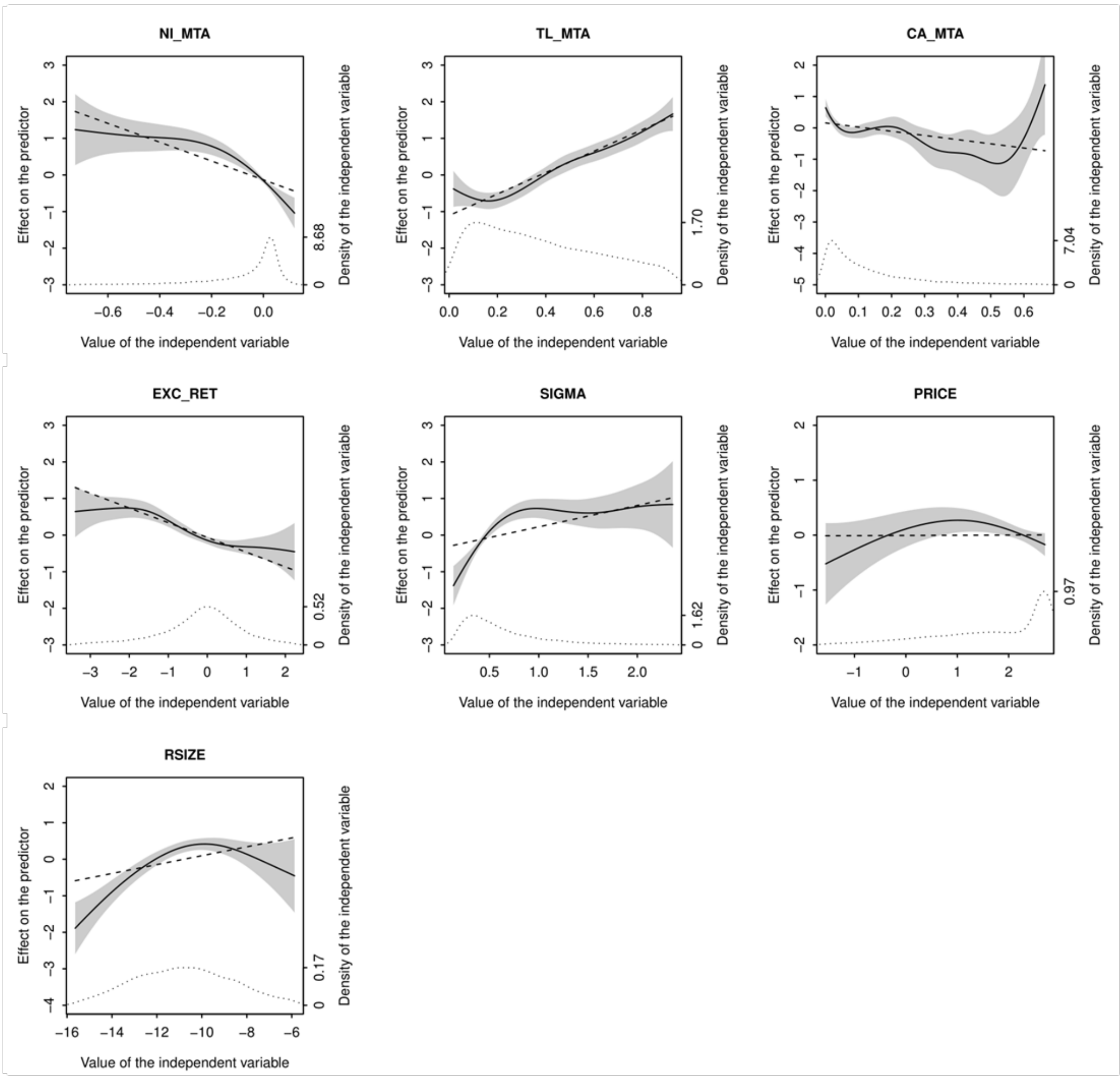

Figure 2.3: Estimated spline patterns of the significant independent variables in GAM3.

2.4.3 Validity and the Total Cost of Misclassification

First, we will compare the GLM and GAM estimations with respect to several goodness-of-fit criteria and we will highlight the relevance of the empirically proven nonlinear relationships to the probability that a company will go bankrupt. The validity of the estimated GLMs and GAMs on the basis of the likelihood that a company will go bankrupt, according to Nagelkerke's pseudo-R^2 (Nagelkerke et al., 1991) and to Akaike's information criterion (Akaike, 1998) can be seen in Table 2.6. In contrast to Nagelkerke's pseudo-R^2, Akaike's information criterion does take into account a model's complexity. This allows us to compare directly the validity of GLMs and GAMs (Horowitz, 1983; Wood, 2017). Nagelkerke's pseudo-R^2 is clearly higher in each GAM than in the corresponding GLM. The increase in Nagelkerke's pseudo-R^2 amounts to 33.82% (GLM1 vs. GAM1), 25.93% (GLM2 vs. GAM2), and 24.66% (GLM3 vs. GAM3). Applying

Akaike's information criterion, according to which lower values indicate greater validity, leads to a similar conclusion. Given that Akaike's information criterion explicitly takes into account a model's complexity, the relative difference between GLMs and GAMs is lower, because the GAM exhibits a larger number of equivalent degrees of freedom. However, the difference according to Akaike's information criterion is sufficiently large to indicate that the GAM is superior to the corresponding GLM (Hilbe, 2009).

Table 2.6 also provides proof of the model's validity on the basis of classification. This is a more reliable indicator of a model's validity with respect to predicting the likelihood of a company going bankrupt. We calculated the AUC, which indicates the model's overall validity (Engelmann, 2006), for both the training and the validation sample. The values we derived from the GAMs exceed those we derived from the GLMs. This applies to both the training and the validation sample. The differences between the values that fall within the AUC are statistically significant. Applying the statistical test that DeLong et al. (1988) recommend, we found that the differences in the training sample and in the validation sample are statistically significant at p-value < 0.001. The results show that the GAM remains superior to the corresponding GLM when the validation sample is used.

In the following, we will estimate the total cost of misclassification by applying the GLM and the GAM estimations to several cost relations $C(0)/C(1)$. For example, the cost relation $C(0)/C(1) = 0.1$ states that the cost $C(1)$ that arises from the misclassification of companies that are actually bankrupt is ten times as high as the cost $C(0)$ that arises from the misclassification of companies that are actually solvent. Altman (2000) has estimated the cost relation at $C(0)/C(1) = 1/35 = 0.029$. Adams and Hand (1999) have calculated that according to banking domain experts the cost relation is in the range of $0.067 = 1/15 \leq C(0/C(1)) \leq 1/6 = 0.167$ with a most likely value of $C(0)/C(1) = 1/10 = 0.1$. As a result, we also take into account the cost relation within the range $C(0)/C(1) \in [0.01; 0.02]$.

Figures 2.4 to 2.6 illustrate the relative difference in the total cost of misclassification between the GLM and the GAM. A positive difference indicates that, compared to the GLM, the GAM produces more accurate results and therefore reduces the total cost of misclassification. We should add that we calculated separately the cost-minimizing threshold probability of bankruptcy for the GLM and for the GAM and for each cost relation. We found that the total cost of misclassification we derived from each GAM was lower than the equivalent cost we derived from the corresponding GLM. The maximum reductions in the total cost of misclassification amount to 15.5% (GLM1 vs. GAM1), 17.7% (GLM2 vs. GAM2), and 17.2% (GLM3 vs. GAM3) with respect to the training sample. Applying the estimated GLMs and GAMs to the validation sample yields similar empirical results. However, the maximum reduction in the total cost of misclassification is in two cases lower and in one case higher and amounts to 13.6% (GLM1 vs. GAM1), 17.1% (GLM2 vs. GAM2), and 18.9% (GLM3 vs. GAM3) with respect to the validation sample.

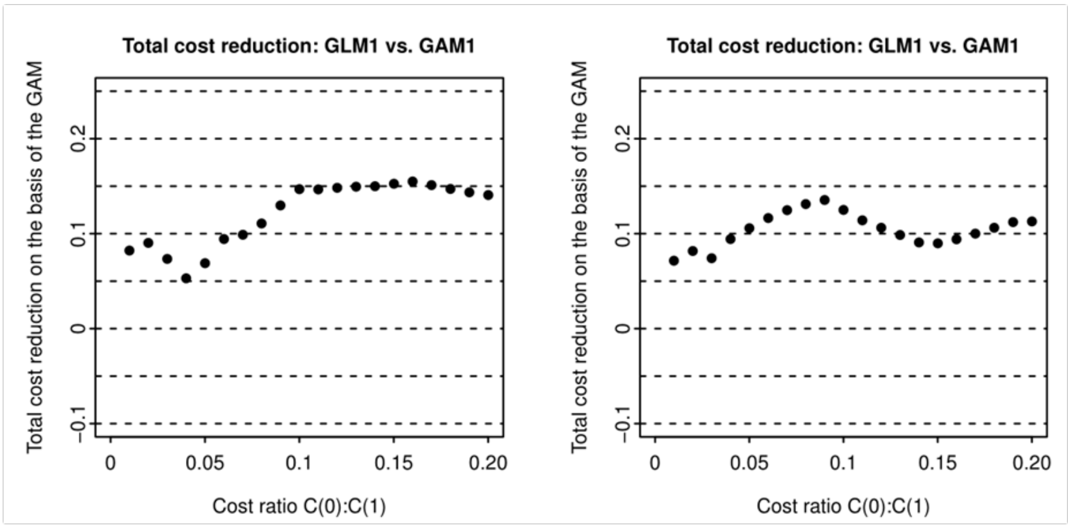

Figure 2.4: Relative differences in the total cost of misclassification between the GLM1 and the GAM1 (left: training sample; right: validation sample).

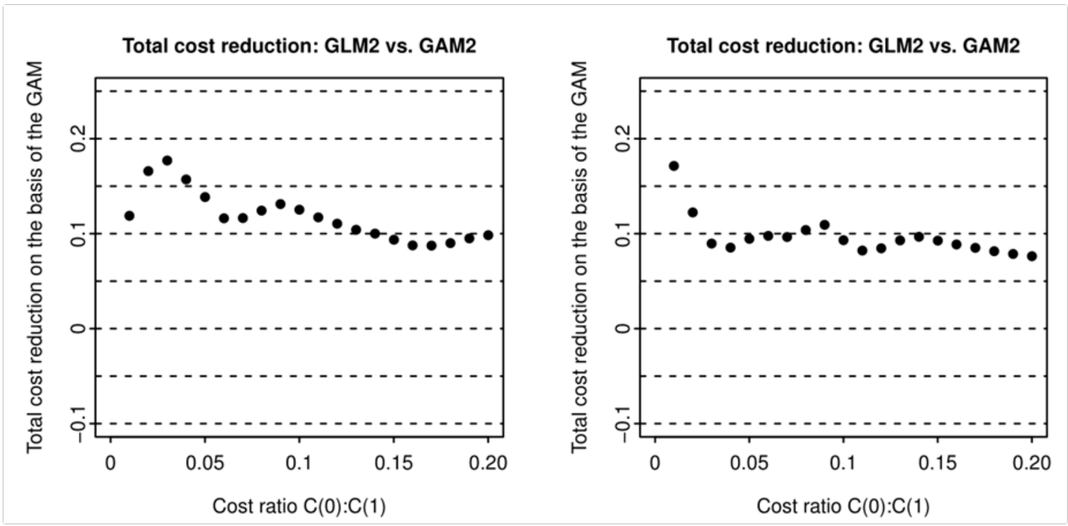

Figure 2.5: Relative differences in the total cost of misclassification between the GLM2 and the GAM2 (left: training sample; right: validation sample).

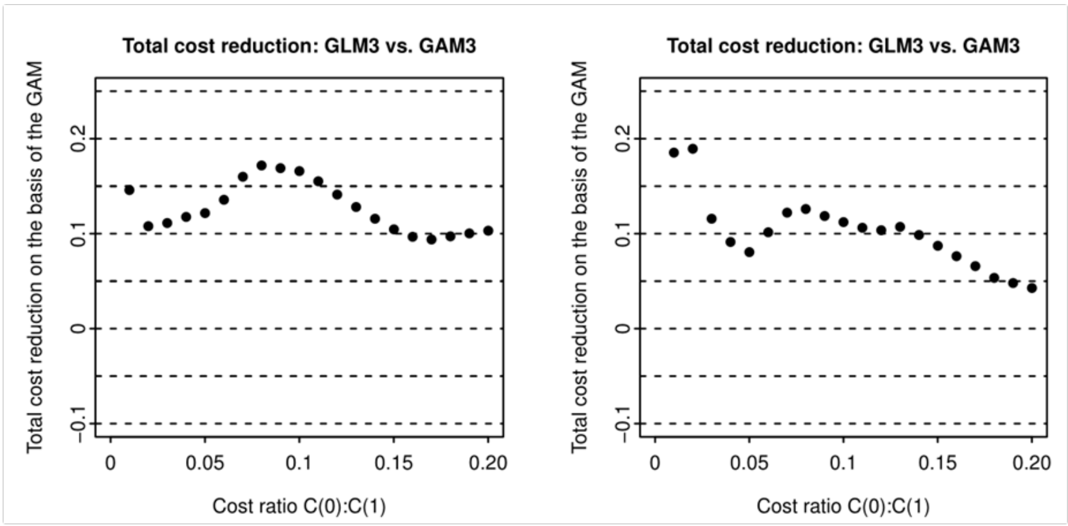

Figure 2.6: Relative differences in the total cost of misclassification between the GLM3 and the GAM3 (left: training sample; right: validation sample).

In Table 2.7 we present a cross-comparison of the relative differences in the total cost of misclassification. The comparison shows that the choice of independent variables and the choice of methodology affect the relative differences in the total cost of misclassification to a similar extent. Table 2.7 indicates that the independent variables that Campbell et al. (2008) used are more informative with regard to predicting bankruptcy than the independent variables that Altman (1968, 2000) used.

Table 2.7: Relative differences in the total cost of misclassification for $C(0)/C(1) = 0.1$.

Training sample	GLM1	GLM2	GLM3	GAM1	GAM2	GAM3
GLM1	0.000	0.164	0.165	0.147	0.268	0.303
GLM2		0.000	0.001	–0.020	0.125	0.167
GLM3			0.000	–0.022	0.124	0.166
GAM1				0.000	0.143	0.184
GAM2					0.000	0.048
GAM3						0.000
Validation sample	**GLM1**	**GLM2**	**GLM3**	**GAM1**	**GAM2**	**GAM3**
GLM1	0.000	0.115	0.159	0.125	0.198	0.253
GLM2		0.000	0.049	0.011	0.093	0.156
GLM3			0.000	–0.040	0.046	0.112
GAM1				0.000	0.083	0.146
GAM2					0.000	0.069
GAM3						0.000

For example, GLM2 reduces the total cost of misclassification resulting from GLM1 by 16.4% (training sample) and 11.5% (validation sample) and GAM2 reduces the total cost of misclassification resulting from GAM1 by 14.3% (training sample) and 8.3% (validation sample). Furthermore, taking into account nonlinear relationships also increases the accuracy of bankruptcy predictions. For example, GAM1 reduces the total cost of misclassification of GLM1 by 14.7% (training sample) and 12.5% (validation sample) and GAM3 reduces the total cost of misclassification of GLM3 by 16.6% (training sample) and 11.2% (validation sample). These results allow us to conclude that selecting appropriate independent variables is as important as taking into account nonlinear relationships. These findings are consistent in both the training and the validation sample.

2.5 Conclusion

In order to derive a reliable prediction of bankruptcy, it is necessary to strike a balance between a model's validity and complexity. In the present study we extend commonly used bankruptcy prediction models by taking into account nonlinear relationships between independent variables and the predictor for the probability of bankruptcy. Omitting the effects of nonlinear relationships may distort the estimates of a company's probability of going bankrupt. This makes it necessary to evaluate the economic relevance of taking into account nonlinear relationships. For that purpose, it is important to select appropriate validity criteria.

Our findings show that several independent variables that Altman (1968, 2000) and Campbell et al. (2008) used have statistically significant and economically plausible nonlinear effects on the probability of a company going bankrupt. In the value range where the independent variables exhibit sufficient data points, it is safe to assume that these variables have an almost linear effect on the predictor. However, we did observe nonlinear relationships below and above specific thresholds at which the estimated spline functions change their slope. With respect to the independent variables $EBIT\_TA$, NI_ATA, NI_MTA, TL_ATA, TL_MTA, and EXC_RET, we were able to prove empirically that when each of these independent variables takes small values, there is a converging effect. Below a certain threshold, decreases in the values of each of these independent variables have only a minor or no effect on the probability that a company will go bankrupt. With respect to the independent variables TL_ATA, EXC_RET, and $SIGMA$, we observed that, above a certain threshold, when these independent variables take large values, there is a similar effect on the probability of bankruptcy.

The validity measures that are based on either likelihood or classification indicate that the validity of the GAMs we used, in which we took into account nonlinear relationships, is higher than that of the equivalent GLMs. As a result, we have to acknowledge that there are relevant nonlinear relationships between the independent variables that were introduced by Altman (1968, 2000) and Campbell et al. (2008) and the predictor. However, the improvements in the validity measures that are based either on likelihood or on classification may not necessarily be perceived as sufficient to justify choosing a more complex model for predicting bankruptcy. When only such measures are used, there is a risk that the evaluation of bankruptcy-prediction models will lead to a wrong conclusion and to choosing an inappropriate model, even if that model reduces the total cost of misclassification on an economically relevant scale. For example, a global, single-item validity measure such as the AUC does not take into account the actual consequences and thus the total cost of misclassification. Consequently, single-item validity measures such as the AUC distort conclusions on validity. To prevent this, it is advisable to evaluate such models on the basis of practical relevant assumptions about the consequences of misclassification.

In the present study we examined whether the amount of reduction in the total cost of misclassification can serve as a further validity criterion. To demonstrate the validity of this criterion, we applied two nested models that differ only with respect to nonlinear relationships: the GAM takes them into account, while the GLM does not. Consequently, we can be confident that any reduction in the total cost of misclassification can be attributed to the inclusion or exclusion of existing nonlinear relationships. With respect to a range of plausible cost relations, we found that applying a GAM clearly reduces the total cost of misclassification in both the training and the validation sample. The increase in the validity of classification in terms of reducing this cost amounts up to 18.9% under assumptions that hold in practical applications.

The results of our analysis are limited by the specific failure criterion that we chose to apply, as well as by the low number of observations in the peripheral areas of the independent variables we examined. The failure criterion we chose relies on the definition of bankruptcy and the prediction horizon. We believe that it should be possible to replicate our results using different criteria of failure; however, further research is needed in order to confirm this supposition. Our study identified nonlinear relationships, particularly in the peripheral areas of the independent variables that we used. However, these nonlinear relationships are based on relatively few observations, so further research is needed in order to investigate whether the nonlinear effects that we identified also hold when different databases are used.

The results of our analysis are also limited by the deterministic and mean cost relations that we assumed. We based our analysis of the total cost of misclassification on given cost relations that are identical in all observations. However, the actual cost relation should be estimated separately for each observation. In the context of bank lending, the cost $C(1)$ results from the misclassification of companies that are actually bankrupt and should correspond to the estimated loss in the case of default. In comparison, quantifying the cost $C(0)$ that arises from the misclassification of companies that are actually solvent is a challenge, because this cost consists in foregone profits, reputational cost, and other opportunity costs. One problem is that the practical fitness of a specific bankruptcy-prediction model can only be evaluated on the basis of a validity measure that considers the total cost of misclassification, rather than a validity measure that is based exclusively on either likelihood or on classification. To resolve this problem, future research and future practical applications will need to examine whether more complex models for predicting bankruptcy also reduce the total cost of misclassification to an economically relevant extent.

Dark Premonitions:
Pre-Bankruptcy Investor Attention and Behavior

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Abstract

Using extensive data on the activity recorded on the Securities and Exchange Commission's EDGAR server, we show that companies that are effectively bankrupt receive 14–23% more attention from investors prior to declaring bankruptcy than peer companies that are financially distressed but remain solvent. This abnormal level of attention is statistically significant during the period of 24 months before bankruptcy. Our analysis shows that a range of market actors, including 82 investment banks, 205 hedge funds, and 272 asset management companies, actively requested filings from the EDGAR server during the period our research covers. We show that professional investors who pay unusual attention to distressed companies that eventually go bankrupt start selling their respective holdings 11–14 months before these companies declare bankruptcy. Our findings suggest that professional investors manage to reduce their losses from bankruptcy considerably by making use of the financial information that distressed companies disclose.

Keywords: Bankruptcy, EDGAR log-file dataset, Form 13F, information gathering and processing, professional investors, propensity score matching, stock selling

JEL classification: C53, D81, G24, G33

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3.1 Introduction

According to the "efficient market hypothesis," stock prices should fully reflect all available information on a company's financial status at any point in time (Malkiel and Fama, 1970; Fama, 1991). If this were the case, investors should not be able to achieve greater returns through gathering and processing such information than they would have done without this information. In this scenario, the probability of a company going bankrupt in the future should also be reflected in its stock price. In turn, this would make the effort to gather and process the information a company discloses in order to predict its probability of going bankrupt worthless for investors.

However, according to Grossman and Stiglitz (1980), a perfectly efficient market where prices fully reflect all available information is unlikely to exist in practice, because no investors would have an incentive to bear the costs of acquiring and processing such information. Research is costly to investors (Grossman and Stiglitz, 1980; Lee and So, 2015; Verrecchia, 1982) and attention is a so-called constrained resource (Kahneman, 1973) that is allocated rationally by (skilled) investors to particular companies (Kacperczyk et al., 2016). As a result, investors should only bear the cost that information gathering and processing involve while this does not exceed the corresponding marginal return (Lee and So, 2015).

The assumption of perfect market efficiency, as these considerations suggest, is rather strict. For that reason, Campbell et al. (1997) proposed the idea of "relative efficiency." The authors argued that the degree of market efficiency is empirically observable and will vary over time (Kim et al., 2011). This line of thought was further developed into the "adaptive markets hypothesis" (Lo, 2004, 2019; Kim et al., 2011), which postulates that the degree of market efficiency fluctuates over time and is governed by market conditions. If the adaptive markets hypothesis is valid, there should be incentives for investors to acquire and process information in order to adapt and react to changing market conditions.

Samuelson (1938) argued that investors acquire disclosed company information to reverse-engineer their private expectations, because gathering and processing information may reveal clues about the financial health of companies. More recent studies provided evidence that analysts can use publicly disclosed information, e.g., on accounting or on insider trading, to predict financial distress and corporate bankruptcies (e.g., Altman 1968; Campbell et al. 2008; Seyhun and Bradley 1997) or to detect fraud (e.g., Beneish 1999; Dechow et al. 2011).

As the evidence outlined above suggests, at least some investors have the skill to draw conclusions about a company's status from the information the company discloses (Kacperczyk et al., 2016). On that basis, we propose that gathering and processing disclosed company information is central to the ability of investors to adapt to a constantly changing environment and to protect themselves from the financial impact of negative events such as bankruptcies. If this is correct, it follows that investors should have a greater incentive to focus their attention on companies that are likely to go bankrupt than on companies that are likely to remain solvent in the foreseeable future.

This reasoning appears to be at odds with the findings of Drake et al. (2020). In their study on all US-listed companies, Drake et al. (2020) showed that professional investors tend to acquire more information on companies and stocks that perform better in the short term than on other companies. However, the sample that Drake et al. (2020) used is skewed towards companies that were likely to remain solvent, which means that their data may have failed to capture the unusual degree of attention investors paid to the companies that eventually went bankrupt.

Extending the empirical findings of Drake et al. (2020), we investigate how much attention professional investors pay to companies that are likely to declare bankruptcy in the near future. Our starting point is that if professional investors indeed focus more on such companies, then we should be able to observe how at least some investors translate the information they gather on such companies into action—in other words, how such information affects the decisions of investors to sell their stock in companies that are highly likely to go bankrupt in the near future. More specifically, we expect that skilled professional investors (Kacperczyk et al., 2016), who are better informed than others, are likely to reduce their shares in companies that are likely to go bankrupt but not in companies that, although financially distressed, will remain solvent. In this scenario, selling leads to positive excess returns in two ways: First, skilled professional investors will earn greater returns if they acquire information on companies that are effectively, though not yet officially, bankrupt than they would have done if they had not acted on the basis of such information. Second, these investors will achieve greater returns than unskilled or less skilled professional investors who only rely on free (and therefore limited), rather than paid (and therefore comprehensive) information on companies (Verrecchia, 1982). Market prices reflect the aggregated amount of information processed by all investors who were active during a given period. Such information, however, only becomes available in part and gradually (Verrecchia, 1982). For that reason, we expect that skilled professional investors start selling their shares in effectively, but not officially, bankrupt companies before stock prices start to decline.

Whether investors gather and process disclosed company information to assess the financial health of a company and, if so, which investors tend to use disclosed information for this purpose remains something of a black box. Our study seeks to shed light on these questions by examining on the micro-level which types of investors can decipher the available information and act so as to avoid making a loss when a distressed company actually goes bankrupt. To the best of our knowledge, no prior study has documented how the way investors search for relevant information and the way they handle the stock of financially distressed companies may change prior to a corporate bankruptcy. The main contribution of our paper to the literature is the insight it offers into the process of gathering the information that a company discloses, processing it to assess the likelihood of that company going bankrupt and selling company stock on the basis of the assessment.

Our analysis is primarily based on the log files of the EDGAR server that the Securities and Exchange Commission (SEC) maintains. These data include detailed information on server traffic; specifically, on requests made for information (e.g., on the volume of requests and the type of filing that was requested) on the SEC filings of US-listed companies in the period February 14th, 2003 to June 30th, 2017. From these data, we were able to collect information on a sample of 2,481 market actors who requested information on company filings held on the EDGAR database. Our analysis of the partly anonymized IP addresses of these actors enabled us to differentiate between investors and other types of actors, as well as between different categories of professional investors on the basis of various criteria, including geographical location. Furthermore, we took care to control for factors that could potentially influence the data (such as certain company characteristics or specific events that occurred in the period of interest) but are not related to bankruptcy.

To derive our final sample of US-listed companies, we used propensity score matching (for an overview, see Shipman et al. (2017)). This allowed us to control satisfactorily for accounting-based and market-based independent variables, a company's industry and the year of observation. Our analysis is based on a subsample of 269 companies that went bankrupt in the period July 1st, 2005 to December 31st, 2016 and five matched subsamples of 269 comparable companies that were financially distressed but remained solvent over the same period. We matched these samples on the basis of the company characteristics that are included in five common bankruptcy prediction models; namely, those developed by Altman (1968), Ohlson (1980), Campbell et al. (2008), Merton (1974) in conjunction with Bharath and Shumway (2004).

The empirical analysis of our refined samples identifies systematic patterns in the search behavior and decisions of market actors with regard to their portfolio of companies. Specifically, we found that market actors, particularly professional investors, gather significantly more information on companies that are effectively, though not yet officially, bankrupt within the 24 months preceding bankruptcy than on comparable companies that are financially distressed but ultimately remain solvent. Furthermore, our analysis of portfolio holdings on the basis of Form 13F filings shows that the number of requests for relevant company information predicts that the investors who have made these requests will sell stock before a company goes bankrupt so as to reduce considerably the financial impact of the anticipated bankruptcy on their returns. Importantly, the same investors do not reduce their holdings in companies that, although financially distressed, remain solvent. Our tests show that this observation is statistically significant and can therefore be attributed to the information that these investors gather and process.

Our findings provide significant practical insights. Professional investors need to utilize efficiently all available resources in order to predict which companies are likely to go bankrupt and act so as to minimize their own loss. Our empirical analysis tracks in detail both the process of gathering information and the changes in portfolio holdings on the micro-level, addressing the question of how investors can use disclosed company information to make the right portfolio decisions. Overall, our empirical results emphasize the importance of disclosed accounting information for predicting bankruptcy, confirming the findings of previous studies such as that by Jones (2017).

Several robustness checks indicate that our results are valid and that none of the other factors we tested can explain the variance in the requests for disclosed company information that we observe. Our findings are also economically plausible: professional investors need to consider carefully opportunity costs when they sell stakes in a company that is likely to go bankrupt ahead of bankruptcy. To limit the financial impact of a bankruptcy event on their portfolio and to avoid opportunity costs, investors need to engage in research. The investors in our sample exhibited significantly different information-gathering and stock-selling behavior when researching companies that eventually went bankrupt and companies that, although distressed, remained solvent. These differences can be seen even in the case of companies that are very similar in other respects. On that basis, we can conclude that conducting this kind of research can be particularly valuable for professional investors.

The paper is structured as follows: In the next section we review the recent research on the attention investors pay to companies, including studies that use the EDGAR log-file dataset. We also outline briefly the research on bankruptcy prediction and our paper's contribution to the literature. In Section 3.3 we introduce the EDGAR log-file dataset and our other sources while in Section 3.4 we discuss in detail our methodology. In Section 3.5 we examine differences in the attention investors pay to companies that are effectively bankrupt and companies that, although financially distressed, remain solvent and how this information affects subsequent decisions on their portfolio holdings. We conclude the paper with an overview of our findings in Section 3.6.

3.2 Literature Review

Research on investor attention initially focused on how the attention investors pay to different categories of companies relates to market responses to periodical events such as earnings announcements. Most of these studies used the volume of relevant Google searches as a proxy for the interest that primarily retail investors show in a company (Chi and Shanthikumar 2017; Da et al. 2011; Drake et al. 2012). Other studies used as a proxy data on the online requests that professional investors carried out on Bloomberg terminals (Ben-Rephael et al., 2017) or data on the frequency with which retail investors logged into their online retirement accounts (Sicherman et al., 2016). The common feature of all of these studies is that they treated the attention that investors pay to companies as a response to disclosed company information.

Another group of studies utilized the SEC's EDGAR log-file dataset. This dataset records details on all requests made to the EDGAR server for disclosed information on US-listed companies and can therefore reveal patterns of research behavior. Consequently, the EDGAR log files are a very promising tool for observing and analyzing how market actors acquire information on companies. Loughran and McDonald (2017) analyzed the EDGAR log-file dataset with respect to requests made for information included in the Form 10-K filings. Drake et al. (2015) have shown that market actors request disclosed filings particularly around the time of important corporate events, such as restatements, earnings announcements and acquisition announcements, or weak stock performance. In a related study, Drake et al. (2016) showed that investors access historical accounting reports in order to understand the context of a corporate event better and to assess more accurately information on a company's actual valuation. Events such as negative earnings announcements or shocks that affect negatively a company's valuation can shape this context and therefore influence the investors' assessment. Iliev et al. (2018) identified requests for information on mutual funds logged on the EDGAR server and found that professional investors engage in a significant amount of governance-related research. As a result of these and similar studies, research on investor attention shifted from examining how investors react to disclosed company information to how investors gather and process relevant information.

Another set of studies examined how the information that investors gather may help predict how a company's success will develop. Drawing on the EDGAR log-file data set,Lee et al. (2015) showed that searches had yielded company data that could help explain cross-sectional variations in company characteristics, such as stock returns and valuation multiples. Similarly, Bauguess et al. (2018) showed that EDGAR users submitted significantly more requests for the filings of peer companies that matched IPOs. The authors also showed that the number of requests for such filings correlated with the respective IPOs' probability of success.

citechen2020iq also used the EDGAR log-file dataset to retrace the patterns of searches for information related to insider-trading filings and to the subsequent trading activities of professional investors. More recently, Gibbons et al. (2020) found that analysts rely on EDGAR for 24% of their estimation updates and that requesting information on EDGAR is associated with a significant reduction in those analysts' forecasting errors. This finding echoes the empirical findings of Cheng et al. (2016), who found that when analysts acquire information directly from a company's website, the accuracy of their forecasts increases. In a more recent study, Drake et al. (2020) analyzed the requests for Form 10-K filings on the EDGAR server that professional investors had submitted and showed that increases in such requests for information on specific companies can predict both unexpectedly better company performance and increases in the investors' holdings in those companies. Overall, the studies we review here indicate that requests submitted to the EDGAR server are a valid measure of investor attention and can also help predict how a company's finances will develop. It follows that this research, to which our study contributes, is also highly relevant to predicting bankruptcy.

The purpose of research on predicting bankruptcy is to help estimate as accurately as possible the probability of a company going bankrupt. The accuracy of such forecasts largely depends on two things: first, the methods and models researchers apply to predict bankruptcy; second, on selecting the most suitable explanatory variables for this purpose (Laitinen and Kankaanpaa, 1999). Several studies in this literature discuss and apply various empirical and statistical methods and models (e.g., Altman and Saunders 1997; Balcaen and Ooghe 2006; Bellovary et al. 2007; Dimitras et al. 1996; Jones 2017; Scott 1981). However, selecting the appropriate explanatory variables is also key to predicting bankruptcy as accurately as possible. The independent variables that many relevant empirical models use fall into four main categories: (a) accounting-based key performance indicators that can be obtained from annual financial statements (Altman 1968; Martin 1977; Ohlson 1980), (b) market-based key performance indicators that can be derived from a company's capital market valuation (Campbell et al. 2008; Shumway 2001), (c) company characteristics, such as industry affiliation (Chava and Jarrow, 2004), shareholder structure (Jones, 2017), management compensation (Jones, 2017), or degree of research and development (Franzen et al., 2007), and (d) the structural and linguistic characteristics of a company's annual report (e.g., length, complexity, and linguistic tone) and the qualitative information it contains (Cecchini et al. 2010; Mayew et al. 2015; Shirata and Sakagami 2008; Shirata et al. 2011; Tennyson et al. 1990). Furthermore, corporate bankruptcies are related to macroeconomic conditions and tend to be highly correlated. Indeed, research on bankruptcy clustering indicates that the probability of bankruptcy increases when short-term interest rates decline (Duffie et al., 2007) or the GDP shrinks (Giesecke et al., 2011) and when the stock market declines or becomes highly volatile (Giesecke et al., 2011). Contagion can also drive bankruptcy clustering, because a company's bankruptcy can have a direct impact on the financial health of other companies and therefore on the likelihood that they too will go bankrupt (Azizpour et al., 2018).

This paper brings together research on the attention professional investors pay to distressed companies and research on selecting appropriate information to predict bankruptcy in the foreseeable future. We draw on the EDGAR log-file dataset to show that companies that are effectively bankrupt and highly likely to become officially bankrupt in the near future receive considerably more attention from professional investors than peer companies that, although financially distressed, ultimately remain solvent. We furthermore show that specific professional investors can utilize disclosed company information to assess which companies will go bankrupt and start selling their holdings in those companies 11–14 months before bankruptcy is declared. These findings can prove valuable for professional investors who are seeking ways of reducing their portfolio risk due to potential bankruptcies. Our empirical findings shed light on the relationship between how professional investors gather relevant information and subsequent changes in their holdings of companies that are likely to go bankrupt.

In some contrast to Drake et al. (2020), who found that the companies on which investors acquire more information subsequently perform better and investors increase their holdings of those companies, we provide empirical evidence that in the case of financially distressed companies more extensive information acquisition predicts bankruptcy and a reduction in the holdings of professional investors. In other words, our study shows that the relationship between professional investor attention and future company performance is not monotonous, because increased attention is not always associated with higher future company performance. In fact, the relationship between the degree of attention and future company performance tends to be U-shaped, because a higher degree of attention is associated with either prospective bankruptcy or with prospective abnormally positive company performance.

Additionally, our study confirms empirically the Grossman–Stigliz paradox (Grossman and Stiglitz, 1980). Specifically, our results indicate that at least some professional investors can interpret disclosed information on financially distressed companies so as to draw the right conclusions. In that respect, our study also extends the work by Kacperczyk et al. (2016), who showed that skilled investment managers rationally allocate their attention on investments. Moreover, as our results indicate that investors adapt to changes in a firms' financial health, we contribute to the literature on adaptive markets (Lo, 2004, 2019; Kim et al., 2011). Specifically, we show that professional investors can detect companies that are effectively, but not yet formally bankrupt and subsequently reduce their holdings in such companies accordingly.

3.3 Data

3.3.1 Data Sources

For the purposes of this study we used three types of data (see Figure 3.1): First, we used data on investor attention, which we derived from the EDGAR log-file dataset, provided by the SEC's Division of Economic and Risk Analysis (SEC DERA). These log files contain details on how market actors access and use company information available on EDGAR, including the partly anonymized IP addresses of users who have accessed the database. We hand-collected the IP addresses of market actors, bots, and institutions in our sample and matched them to the data they had retrieved from EDGAR. Furthermore, to determine the geographical location from which individual requests had been made to the EDGAR server, we used the GeoIP database, which is provided by MaxMind.

Second, we used company-specific information, including accounting data derived from the Compustat database, information relating to stock prices, which was derived from the CRSP database, and information on bankruptcies, derived from the UCLA–LoPucki Bankruptcy Research Database, and from the bankruptcy database that Sudheer Chava has built and maintains (Chava and Jarrow, 2004; Chava et al., 2011). Third, we used data on investor holdings, which we derived from Form 13F filings. We used company-specific information primarily to select our sample of companies and to match companies that became bankrupt to peer companies that remained solvent. To study the attention specific investors paid to the companies in our sample and to analyze their holdings in these companies, we drew on the EDGAR log-file dataset.

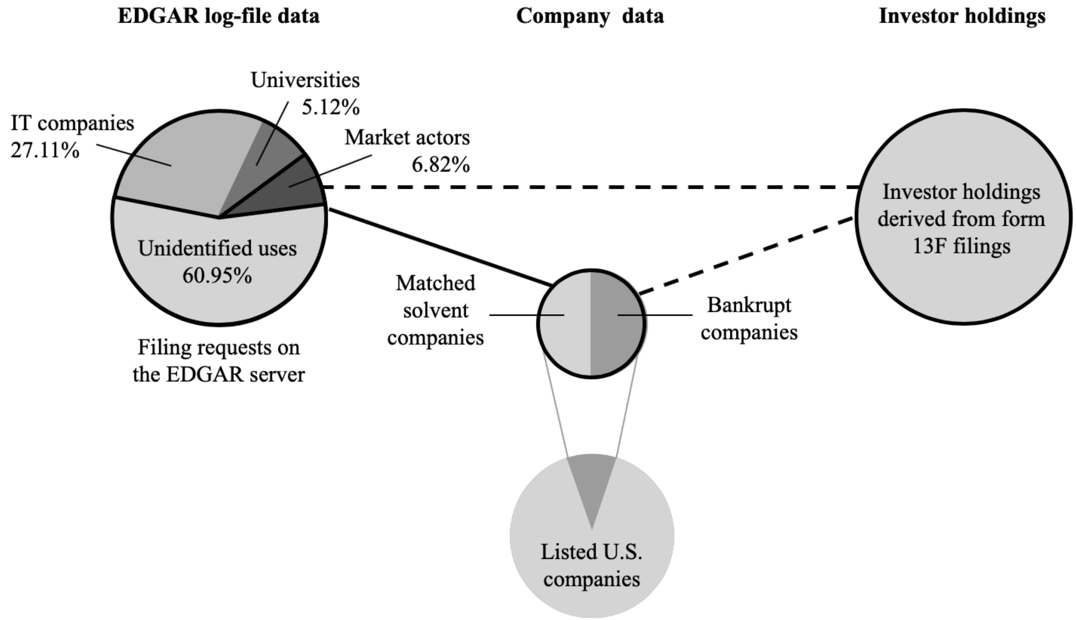


Figure 3.1: This figure illustrates the relationship between the sources of data we use in this paper. To derive our samples of bankrupt and solvent companies, we applied propensity score matching, based on company-specific accounting and market data (see Section 3.4). We drew our accounting and market data from the entire US CRSP/Compustat universe. To measure the level of attention that investors paid to the bankrupt and solvent companies in our samples (see Section 3.5), we draw on the EDGAR log-file dataset. The filing requests from identified market actors are a subset of this dataset. We additionally examined individual company–investor combinations, matching the investor holdings derived from Form 13F filings to identified professional investors and bankrupt and matched solvent companies.

3.3.2 SEC EDGAR Log-File Dataset

The SEC's Division of Economic and Risk Analysis (SEC DERA) makes available the EDGAR log-file dataset, which contains information on how EDGAR filings are accessed. We collected data covering the period July 1st, 2003 to June 30th, 2017 on all US-listed companies in the EDGAR database. We selected July 1st as our start date because the number of logged requests had been rising significantly up to that point and only leveled off after June 2003.

Among other information, the EDGAR log-files register the partly anonymized Internet Protocol (IP) address of the user who has accessed a particular filing, the timestamp of the request, and the accession number that the SEC has assigned to the requested filing. The EDGAR log-files that we consulted document a total of about 13.7 billion requests that were submitted to the server within the period from February 14th, 2003 to June 30th, 2017 (see Table 3.15 in Appendix 3.A). The last portion (i.e., octet) of each logged IP address is ciphered to ensure relative anonymity (e.g., 192.168.2.cpi). Every electronic device that can connect to the internet and uses the IP protocol is assigned an IP address that encodes information about (a) the host or network that a device is part of and (b) the geographical location of the host to which this device is connected. To identify the market actors that used a specific IP address to request data from the EDGAR server, we followed mainly the procedure that Bozanic et al. (2017) describe.

Organizations that implement a single policy for accessing external internet network addresses are called Autonomous Systems (ASs). An AS consists of a block of IP addresses under the same prefix or prefixes. Classless Inter-Domain Routing (CIDR) is a relatively new method of representing IP addresses. According to CIDR notation, an IP address or routing prefix consists of a suffix that indicates the number of bits in that prefix, e.g., 192.0.1.0/22. Using CIDR makes it possible to allocate blocks of IP addresses to organizations. To identify the organizations from which specific requests to the EDGAR server had been made, we hand-collected a comprehensive sample of AS numbers and IP address blocks that represent the full range of all 256 possible IP addresses in an entire 24-bit CIDR block. If an entire 24-bit CIDR block is assigned to an organization, it is possible to identify requests to the EDGAR server that have been made from any of all possible IP addresses, ranging from xxx.xxx.xxx.0 to xxx.xxx.xxx.255, allocated to that organization. This enabled us to identify the organizations from which specific requests had been made, though not departments or individuals that had submitted those requests.

To collect as many relevant IP addresses as possible, we identified all potential entities that might have accessed EDGAR. For example, we searched for all entities that ever filed a Form 13F, banks, pension funds and insurance companies listed in Thomson Reuters, all broker dealers (we obtained a list from SEC) and market makers (we obtained lists from NYSE and NASDAQ), as well as bots (i.e., software that companies program to access automatically data, such as filings, on servers). Making use of this information, we identified 2,481 market actors that made requests for filings to the EDGAR server in the period of interest (see Table 3.1). This sample represents a broad variety of professional investors and other market actors, enabling us to distinguish between institutions that request a filing for investment analysis, i.e., investment banks, hedge funds, and asset management companies, and institutions that request a filing for other purposes, i.e., data providers or law firms. As a result of this approach, we were able to classify the entities that made the requests with greater precision than Lee et al. (2015), Loughran and McDonald (2017), and Drake et al. (2015). Lee et al. (2015) classified as "robots" (i.e., bots) all IP addresses from which more than 50 requests for filings had been sent within 24 hours, while Drake et al. (2015) used a different criterion; namely, more than five requests per minute or more than 1,000 requests in 24 hours. In a more recent study Chen et al. (2020) excluded logs connected to IP addresses that had requested more than 1,000 filings within 24 hours.

Table 3.1: The table presents the summary statistics on the requests for information made by identified market actors to the EDGAR server. By far the most requests were submitted by investment banks, data providers, hedge funds, asset management companies, and terminal providers. In total, we identified 2,481 market actors that requested information on the EDGAR server in the period February 2003 to June 2017. The requests submitted by identified market actors account for 6.82% of all requests in our dataset.

Market actor categories	No. of identified market actors	No. of identified IP address blocks	Total requests	Share in total requests	Share in requests made by identified market actors
Investment banks	82	10,567	276,816,922	2.02%	29.60%
Data providers	19	2,529	225,540,662	1.65%	24.12%
Hedge funds	205	1,290	172,668,612	1.26%	18.46%
Asset management companies	272	4,190	85,089,787	0.62%	9.10%
Terminal providers	3	452	84,030,887	0.61%	8.99%
Banks	806	10,936	22,860,929	0.17%	2.44%
Financial regulators	26	4,193	15,091,702	0.11%	1.61%
Insurance companies	234	7,169	14,160,410	0.10%	1.51%
Publishing companies	179	3,853	13,786,052	0.10%	1.47%
Private equity	59	681	8,983,086	0.07%	0.96%
Governments	332	52,082	7,651,523	0.06%	0.82%
Broker dealers & market makers	107	863	4,403,756	0.03%	0.47%
Prop traders	36	378	2,223,866	0.02%	0.24%
Stock exchanges	42	854	779,151	0.01%	0.08%
Pension funds	44	408	775,861	0.01%	0.08%
Mortgage & loan providers	35	132	296,889	0.00%	0.03%
Total	2.481	100,577	935,160,095	6.82%	100%

We classified each identified market actor into one of a total of 16 categories. Table 1 presents the descriptive statistics on the requests each market actor category submitted to the EDGAR server. The market actors we identified account for 6.82% of all requests contained in the EDGAR log-file dataset. The most important and possibly the most interesting categories are investment banks, hedge funds, and asset management companies. The 559 individual market actors we identified in these three groups made a total of 534,575,321 requests to the EDGAR server in the period of interest. To interpret the figures more precisely, we analyzed the requests submitted from 18 IT companies, including Alphabet, Microsoft, and Yahoo, and found that these companies account for 27.11% of all requests submitted to the EDGAR server within the entire period of interest (see Table 3.16 in Appendix 3.A). Universities are another group of heavy users that access data on EDGAR. We identified 1,102 universities that made 5.12% of all requests logged on the EDGAR server. In total, the actors in our sample made 39.05% of all requests logged on EDGAR within the period our study covers.

In Table 3.17 (Appendix 3.A), we report the 20 most commonly accessed types of form filings and the total requests made for each type form. As the table shows, Form 4 is the most frequently accessed category of filings (40.18% of all requests). Other frequently accessed categories include Form 8-K, Form 10-Q, and Form 10-K filings. In total, these four form types account for 77.47%

of all requests. Our data reveal that different types of actors are interested in different types of filings. More precisely, only 3.10% of all requests made by hedge funds concerned Form 10-K filings and only 5.60% concerned Form 10-Q filings. In comparison, 10.00% of all requests made by investment banks and 6.61% of all requests made by asset management companies concerned Form 10-K, while 10.45% and 8.22% respectively concerned Form 10-Q filings. With regard to Form 4 filings, they account for 64.87% of all requests made by hedge funds, 53.76% of all requests made by investment banks, and 52.57% of all requests made by asset management companies. In contrast, with regard to Form 8-K filings, the differences between investment banks (10.33%), hedge funds (11.32%), and asset management companies (11.10%) are very small.

We additionally matched the IP addresses contained in the EDGAR log-file dataset to 30 major financial centers from which requests to the EDGAR server were made. For that purpose, we used data on the longitude and latitude that we derived from the publicly accessible MaxMind GeoIP database. The data obtained from this database enabled us to identify the geographical location of all IP addresses contained in the EDGAR log-files. Table 3.18 in Appendix 3.A provides an overview of the requests that were made from major financial centers (radius 18.6 miles or 30 km, respectively). By far the most important financial center is New York City, which accounts for 29.07% of all requests made to EDGAR in the period of interest. Overall, all six US financial centers that we identified dominate the results: collectively, they represent 60.21% of all requests made to EDGAR from a financial center in our sample. The remaining top-ten financial centers are Shanghai, Beijing, Paris, and Toronto.

3.3.3 Company Data

The company data we use in our study include accounting-based and market-based information on US-listed companies. These data were sourced from the merged CRSP and Compustat databases and cover the entire observation period. We used accounting-based and market-based company information to derive the final samples by means of propensity score matching and to estimate our bankruptcy prediction models.

The data we collected on corporate bankruptcies among US-listed companies correspond to the period spanning the fiscal years 1984–2016. We derived these data from the UCLA–LoPucki Bankruptcy Research Database and from Sudheer Chava's bankruptcy database (Chava and Jarrow, 2004; Chava et al., 2011). Both databases show when a company filed for bankruptcy and whether it did so under Chapter 7 or Chapter 11. We matched the data on corporate bankruptcies with information we derived from the merged CRSP/Compustat annual universe.

We applied two criteria: first, there should be available information on a company's stock price until the date that company filed for bankruptcy; second, a company needed to have published an annual financial statement within the 15 months preceding that date.

Given that we analyze filing requests issued within the 24 months preceding and the 6 months following a bankruptcy, the bankruptcies we included in our sample span the period July 1st, 2005 to December 31st, 2016. However, we also used information on bankruptcies that were declared between January 1st, 1983 and June 30th, 2005 to estimate the bankruptcy prediction models we used to validate our results. However, we excluded from our sample all bankrupt companies in the category "Money & Finance" of the Fama–French 12-industry classification scheme. On the basis of our data, we identified 269 bankruptcies that were declared in the period July 1st, 2005 to December 31st, 2016 and 611 bankruptcies in the period January 1st, 1983 and June 30th, 2005 for which we had the complete data we needed in order to define the independent variables of our bankruptcy prediction models..

3.3.4 Form 13F Holdings

We searched the EDGAR database and collected all Form 13F stock holdings reported by the investment banks, hedge funds, and asset management companies we could link to requests entered in the log files. As we manually searched for the IP addresses of all companies that had ever filed a Form 13F, we were able to link directly specific holdings to specific investors who had queried the EDGAR database. We excluded all holdings that were not reported as "common stock," "common equity," or "class A shares." We furthermore matched the identified holdings to data on the CRSP/Compustat database. For that purpose, we used CUSIP-6, which is the only identifier that is consistently reported in all Form 13F filings.

3.4 Sample Construction

3.4.1 Refine and Validate the Final Samples

The first question this study attempts to answer is whether market actors investigate to a greater extent companies that later on file for bankruptcy than companies that remain solvent. To exclude other factors that might explain such a pattern in behavior, we controlled for key financial-performance indicators, including a company's industry and the year to which each observation corresponds. For that purpose, we created two samples of structurally similar US-listed companies: the first sample comprises companies that went bankrupt within the period July 1st, 2005 to December 31st, 2016 (i.e., the "treated" companies), while the second sample comprises comparable companies that, although financially distressed, remained solvent (i.e., "matched" companies).

To define the sample of companies that, although financially distressed, remained solvent, we used propensity score matching. This method, which was introduced by Rosenbaum and Rubin (1983) (for an overview, see Leite (2017)), allowed us to match each bankrupt company to a similarly distressed but solvent company in the same industry (according to the SIC 1 classification scheme) for which we could gather data for the same year. As further criteria for pairing companies, we used independent accounting-based and market-based variables that we derived from five different bankruptcy prediction models. Through this process, we constructed five samples of non-treated companies that are equal in size, comprising 269 observations. We matched the non-treated companies in each sample to the treated companies on the basis of specific characteristics (see Figure 3.2) that reflect a company's industry (according to the SIC 1 classification), its likelihood of going bankrupt, and the year of the observation. The main difference between the sample of bankrupt companies and the five matched samples of solvent companies is that the latter comprise companies that, although financially distressed, remained solvent.

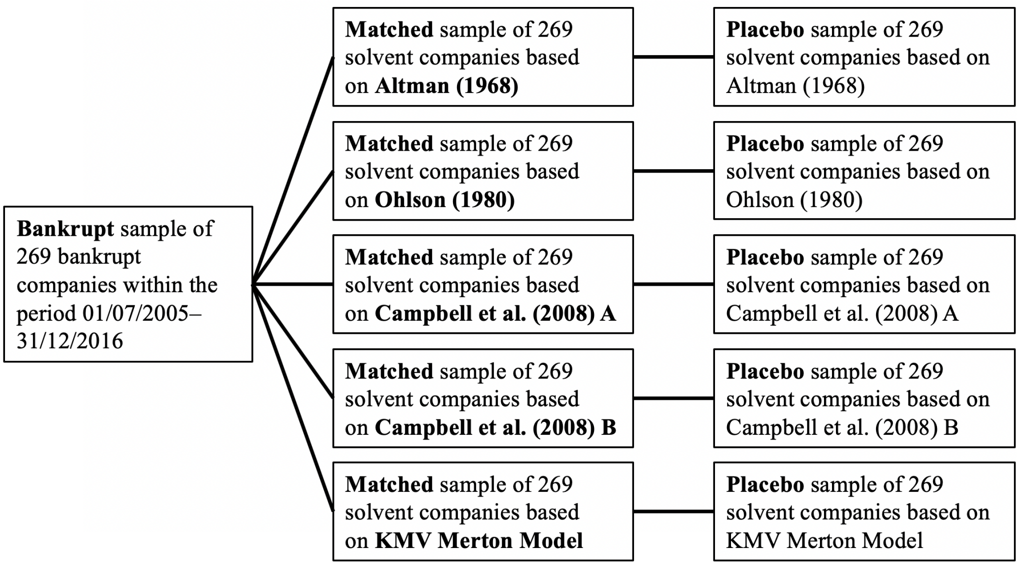


Figure 3.2: This figure depicts the five samples of companies that, although financially distressed, remained solvent. To derive the five samples, we applied various matching criteria, based on five different bankruptcy prediction models. We identified 269 bankrupt companies within the period July 1st, 2005 to December 31st, 2016 and matched them to solvent companies on the basis of the independent variables derived from each of the five bankruptcy prediction models we applied; namely, Altman (1968), Ohlson (1980), Campbell et al. (2008) A and B, and Merton (1974). For the purposes of validation and robustness, we additionally constructed one matched placebo sample for each matched sample. We therefore obtained one sample of 269 bankrupt companies, five matched samples, and five placebo samples.

Selecting appropriate accounting-based and market-based variables as matching criteria that relate to specific bankruptcy prediction models is subjective. The choice of the matching criteria determines the composition of the sample of matched companies. It follows that different sets of matching criteria will lead to different samples of matched companies. To ensure that the choice of the matching criteria does not influence the composition of the samples of matched companies, we used accounting-based and market-based independent variables derived from the bankruptcy prediction models of Altman (1968), Ohlson (1980), Campbell et al. (2008), and Merton (1974) to define the five sets of criteria we applied to match treated to non-treated companies. In the following, we denote the two models we derived from Campbell et al. (2008) as models A and B. In Table 2 we present the independent variables that Altman (1968), Ohlson (1980), Campbell et al. (2008), and Merton (1974) used. As we only use metric accounting-based or market-based independent variables as matching criteria, we did not include the categorical independent variables $OENEG$ and NI_TWO (Ohlson 1980).

Table 3.2: This table provides an overview of the matching criteria we used for propensity score matching. The categorical variables $OENEG$ and NI_TWO were derived from Ohlson (1980). We also used these independent variables to estimate the bankruptcy prediction models we applied for validation purposes.

	Altman (1968)		
WC_TA	Working capital divided by total assets	RE_TA	Retained earnings dividend by total assets
$EBIT\_TA$	Earnings before interest and taxes divided by total assets	MVE_TL	Market value of equity divided by total liabilities
S_TA	Sales divided by total assets		
	Ohlson (1980)		
TL_TA	Total liabilities divided by total assets	$OENEG$	Categorical variable: 1 if total liabilities exceeds total assets; 0 otherwise
WC_TA	Working capital divided by total assets	CL_CA	Total current liabilities divided by total current assets adjusted
NI_TA	Net income divided by total assets	NI_TWO	Categorical variable: 1 if net income is negative for the last two years; 0 otherwise
FU_TL	Funds from operations total divided by total liabilities	CH_NI	Change in net income divided by the total of the current and previous absolute net income
$RSIZE$	Relative company size based on each firm's market valuation (measured as the log ratio of its market capitalization to that of the S&P 500 Index)		
	Campbell et al. (2008) A		
NI_TAA	Net income divided by adjusted total assets	TL_TAA	Total liabilities divided by adjusted total assets
EXC_RET	Annualized 50-trading-days log excess return on each firm's equity relative of the S&P 500 Index	$SIGMA$	Annualized standard deviation of each firm's daily stock return over the past 50 days
$RSIZE$	Relative company size based on each firm's market valuation (measured as the log ratio of its market capitalization to that of the S&P 500 Index)		
	Campbell et al. (2008) B		
NI_MVTA	Net income divided by market-valued total assets	TL_MVTA	Total liabilities divided by market-valued total assets
CA_MVTA	Liquid assets divided by market-valued total assets	MB	Market-to-book ratio
EXC_RET	Annualized 50-trading-days log excess return on each firm's equity relative to the S&P 500 Index	$SIGMA$	Annualized standard deviation of each firm's daily stock return over the past 50 days
$RSIZE$	Relative company size based on each firm's market valuation (measured as the log ratio of its market capitalization to that in the S&P 500 Index)	$PRICE$	Price per share measured as the log and truncated above at \$15
	Merton (1974)		
MVA	Market value of assets	MVE	Market value of equity
$SIGMA\_MVA$	Volatility of the market value of assets	$SIGMA\_MVE$	Volatility of the market value of equity

To verify the reliability of our empirical results, we additionally constructed five placebo samples, matching another sample of solvent but financially distressed companies to each of the five already matched samples (see Figure 3.2). To match each placebo sample to each of the already matched samples, we followed exactly the same matching procedure as previously and applied the same matching criteria.

3.4.2 Propensity Score Matching

The main reason for applying propensity score matching was to pair companies that had gone bankrupt with comparable solvent companies that appeared to be facing a similar bankruptcy risk at the same point in time as their peers that eventually went bankrupt. To match a bankrupt company with a solvent company, we used the Mahalanobis distance measure (see Mahalanobis (1936)). As a result of this procedure, we ensured that the values of the metric independent accounting-based and of the market-based variables in each of the five bankruptcy prediction models are as similar as possible, both in the case of the bankrupt companies and of their solvent matches. An additional criterion was that both matched companies belonged to the same SIC 1 industry category and that the year of observation was the same. We matched the companies on a 1:1 basis without replacement and without caliper bandwidth, in order to keep all 269 bankrupt companies in the final sample and to ensure that all matched samples are equal in size.

Table 3.19 in Appendix 3.B lists the mean values of the metric accounting-based and market-based variables for the bankrupt and matched solvent companies, the p-values of the t-test and the mean caliper distance. The p-values indicate that there are no statistically significant differences for almost any of the metric variables. Additionally, the mean caliper distances obtained for the 269 matched pairs in each of the five samples fall invariably within the caliper band that Rosenbaum and Rubin (1983) recommend. According to these authors, the caliper distance should be less than or equal to 0.25 of the standard deviation of the variable that serves as a matching criterion. In our case, the mean caliper distances are in the range 0.00–0.23.

With respect to the financial metrics, the bankrupt and matched companies are highly comparable. Although all five matched samples include companies that experienced financial distress, the extent to which the samples of matched solvent companies overlap is low. Table 3.3 shows which companies have been included in two of the five samples. The maximum share of overlapping solvent companies is 39% when the metric independent variables of Campbell et al. (2008) A and Campbell et al. (2008) B are used for matching as the matching criteria are comparable.

However, the five samples of solvent but financially distressed companies are heterogeneous and differ with regard to their composition. On these grounds, we can conclude that any effects that are predominantly manifested in those samples will not be random and will not result from the potentially subjective selection of the matching criteria.

Table 3.3: This table shows in a sample-pairwise comparison the extent to which the samples of matched solvent companies overlap. The data show that only a small percentage of solvent companies has been included in at least two matched samples. This indicates that the level of heterogeneity in all five samples is satisfactory.

	Altman (1968)	Ohlson (1980)	Campbell et al. (2008) A	Campbell et al. (2008) B	Merton (1974)
Altman (1968)	1.00				
Ohlson (1980)	0.21	1.00			
Campbell et al. (2008) A	0.24	0.37	1.00		
Campbell et al. (2008) B	0.23	0.29	0.39	1.00	
Merton (1974)	0.18	0.25	0.27	0.30	1.00

3.4.3 Matching Validation

To validate the results we derived from propensity score matching, we estimate five bankruptcy prediction models that were introduced by Altman (1968), Ohlson (1980), Campbell et al. (2008) and Merton (1974) respectively for Period I, i.e., January 1st, 1983 to June 30th, 2005, and Period II, i.e., April 1st, 2004 to December 31st, 2016. For Period I, the refined data consist of 68,519 firm–year observations recorded between January 1st, 1983 and March 31st, 2004 and 611 bankruptcies recorded between January 1st, 1983 and June 30th, 2005. Similarly, for Period II, the refined data comprise 36,056 firm–year observations recorded between April 1st, 2004 and September 30th, 2015 and 269 bankruptcies recorded between July 1st, 2005 and December 31st, 2016. Figure 3.3 summarizes visually the in-sample and out-of-sample datasets, while Table 3.21 in Appendix 3.B displays the mean and median values of the independent variables used in the models. The dependent variable is company bankruptcy. A company j is classified as "bankrupt" (y_j=1) if it filed for bankruptcy under Chapter 7 or Chapter 11 within 15 months after the most recent balance-sheet date on the annual financial statement that we consulted.

To predict a company's probability of going bankrupt, we used the coefficients we obtained from our models for periods I and II. In Appendix 3.C we describe in detail the methodology we applied to estimate the bankruptcy prediction models. The pseudo-R^2 and AUC values we obtained from the bankruptcy prediction models for the in-sample and out-of-sample estimations, as well as the AUC values for the in-sample estimations of the KMV Merton model (see Merton (1974) and Bharath and Shumway (2004)), are reported in Table 3.22. The validity measures show that every estimated model can distinguish accurately between bankrupt and solvent companies. Indeed, the results of the estimated bankruptcy prediction models are completely in line with the results of Altman (1968), Ohlson (1980), and Campbell et al. (2008).

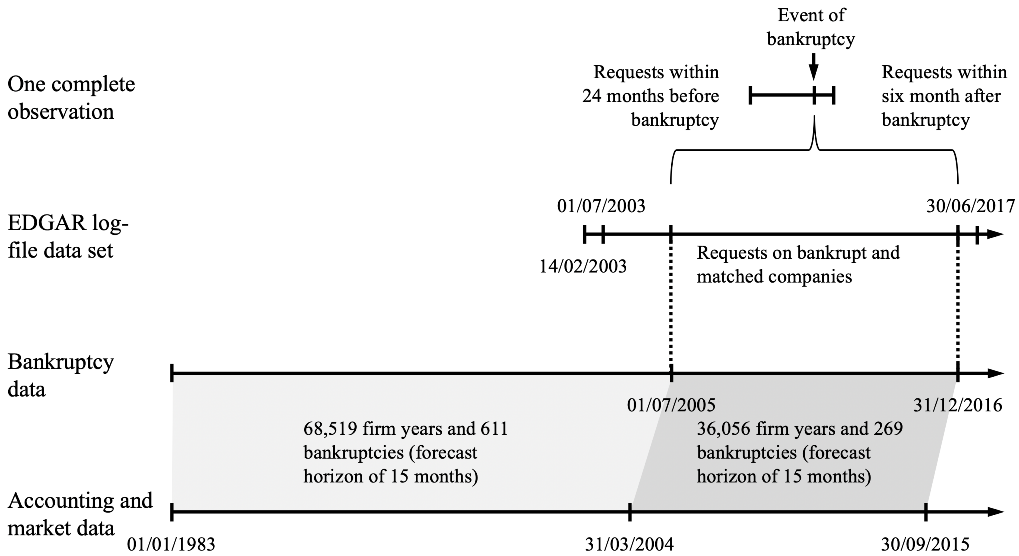


Figure 3.3: The figure presents our in-sample and out-of-sample dataset. Accounting, market and bankruptcy data are available for the entire period. We use bankruptcy data for the period January 1st, 1983 to July 1st, 2005 and accounting and market data for the period January 1st, 1983 to March 31st, 2004 to estimate the out-of-sample bankruptcy model, as our forecast horizon for bankruptcy prediction spans 15 months. We selected the end date of the out-of-sample period on the basis of the availability of EDGAR log-files. These log-files are sparse until July 1st, 2003. However, we need such files for the period spanning 24 months before bankruptcy; therefore, the in-sample period starts on July 1st, 2005. The end of the in-sample period is also determined by the availability of the EDGAR log-files. As these files are only available until June 30th, 2017 and we need such files for a period of at least six months after bankruptcy, the in-sample period ends on December 31st, 2016. Within the period July 1st, 2005 to December 31st, 2016, we observe 269 bankruptcies, which we include in our analysis.

In the next step, we applied the estimated bankruptcy prediction models both to the samples of bankrupt companies and their solvent matches. If the results we obtained from propensity score matching are valid, these models should fail to differentiate between bankrupt companies and companies that, although financially distressed, remained solvent. This is indeed what we found, as Table 3.4 shows. For example, applying model Altman (1968) I to the bankrupt and matched solvent companies and using as matching criteria the same independent variables that Altman (1968) used yields an AUC value of 0.57. The AUC values for all estimated models are in the range 0.57–0.64.

Overall, the obtained AUC values are only slightly above 0.5, indicating that the bankruptcy prediction models do not discriminate satisfactory between bankrupt companies and their solvent matches. However, the composition of the subsamples of bankrupt companies and their solvent matches does allow the models to discriminate between these two categories to some extent. This is because, although both categories of companies are financially distressed, the distributions of the estimated probabilities of bankruptcy that relate to the companies that are effectively, but not yet officially bankrupt (y_j=1) are positively skewed (see Table 3.4). In sum, the matched samples we obtained through propensity score matching are valid; however, there are slight differences in the distributions of the estimated probabilities of bankruptcy between bankrupt companies and their solvent matches.

Table 3.4: This table reports the AUC values and the distribution of the estimated probabilities of bankruptcy for all companies in each of the five samples of 269 bankrupt and 269 solvent companies. The AUC values indicate that none of the models can discriminate sufficiently between the two groups of companies. However, in the sample of bankrupt companies, the distribution of the estimated probabilities of bankruptcy is slightly positively skewed.

Probabilities of bankruptcy		0.1		0.3		0.5		0.7		0.9	
	AUC	y_j=1	y_j=0	y_j=1	y_j=0	y_j=1	y_j=0	y_j=1	y_j=0	y_j=1	y_j=0
Altman (1968) I	0.57	0.01	0.01	0.07	0.10	0.46	0.56	0.85	0.92	1.00	1.00
Altman (1968) II	0.58	0.04	0.05	0.12	0.15	0.46	0.57	0.77	0.85	0.97	1.00
Ohlson (1980) I	0.61	0.05	0.04	0.17	0.29	0.39	0.54	0.72	0.81	0.98	1.00
Ohlson (1980) II	0.60	0.08	0.12	0.21	0.37	0.40	0.54	0.64	0.76	0.92	0.97
Campbell et al. (2008) A I	0.59	0.04	0.04	0.18	0.25	0.42	0.54	0.73	0.86	0.99	1.00
Campbell et al. (2008) A II	0.58	0.09	0.10	0.25	0.33	0.42	0.54	0.63	0.78	0.93	0.98
Campbell et al. (2008) B I	0.64	0.04	0.08	0.19	0.33	0.39	0.59	0.61	0.83	0.97	1.00
Campbell et al. (2008) B II	0.63	0.10	0.17	0.25	0.40	0.38	0.57	0.55	0.78	0.87	0.95
Merton (1974) II	0.59	0.26	0.34	0.39	0.51	0.70	0.82	0.97	0.99	1.00	1.00

3.4.4 Placebo Samples

To increase the reliability of our subsequent analysis, we created placebo samples by applying propensity score matching a second time. Again, we used the same sets of independent variables as matching criteria and stipulated that the industry (according to the SIC 1 classification) and the year of observation have to be identical for both companies in each pair. This procedure yielded five placebo samples, each of which matched the five samples of already matched companies we derived when we first applied propensity score matching (see Figure 3.2). Table 3.20 in Appendix 3.A shows the mean values of the metric accounting-based and market-based independent variables for both the first five samples of matched companies and for the placebo companies. The table also displays the p-values of the t-test and the mean caliper distance. The p-values indicate that the statistical differences that almost all metric accounting-based and market-based independent variables exhibit are not or only weakly significant. Furthermore, our analysis shows that the mean caliper distances of the 269 matched pairs in all five samples are in the range 0.01–0.22.

The matched companies and the placebo companies exhibit comparable company characteristics. Although all five placebo samples include companies that experienced financial distress, again, the extent to which the samples of matched solvent companies overlap is low. Table 3.5 shows which companies have been included in two of the five placebo samples. Using the metric accounting-based and market-based independent variables that we derived from Campbell et al. (2008) A and Campbell et al. (2008) B produces the largest overlap between any two samples, which is 21%. As Table 3.5 shows, the five placebo samples are largely heterogeneous.

Table 3.5: This table shows in a sample-pairwise comparison the extent to which the samples of matched placebo companies overlap. The data indicate that the overlap among the five placebo samples is slightly lower than among the five matched samples of solvent companies (see Table 3.3). This may be because the overall level of financial distress is slightly lower and therefore the pool of potentially matching companies is larger in the placebo samples than in the matched samples.

	Altman (1968)	Ohlson (1980)	Campbell et al. (2008) A	Campbell et al. (2008) B	Merton (1974)
Altman (1968)	1.00				
Ohlson (1980)	0.15	1.00			
Campbell et al. (2008) A	0.16	0.19	1.00		
Campbell et al. (2008) B	0.14	0.14	0.21	1.00	
Merton (1974)	0.10	0.12	0.15	0.17	1.00

Table 3.6 indicates to what extent the estimated bankruptcy prediction models can distinguish between matched and placebo companies. Overall, the AUC values are again slightly above 0.5, which indicates that these models cannot discriminate adequately between the matched and the placebo companies. However, because of the composition of the two subsamples, the models have some discriminatory power. The distributions of estimated probabilities of bankruptcy that relate to the matched companies (y_j=1) are positively skewed. As a result, in this case too there are slight differences in the distributions of the estimated probabilities of bankruptcy between the subsamples of matched and placebo companies.

Table 3.6: This table reports the AUC values and the distribution of the estimated probabilities of bankruptcy for all companies in each of the five samples of 269 matched and 269 placebo companies. The AUC values indicate that none of the models can discriminate sufficiently between the two groups of companies. However, in the sample of matched companies, the distribution of the estimated probabilities of bankruptcy is slightly positively skewed.

Probabilities of bankruptcy		0.1		0.3		0.5		0.7		0.9	
	AUC	y_j=1	y_j=0	y_j=1	y_j=0	y_j=1	y_j=0	y_j=1	y_j=0	y_j=1	y_j=0
Altman (1968) I	0.54	0.01	0.01	0.07	0.09	0.48	0.52	0.90	0.94	1.00	1.00
Altman (1968) II	0.56	0.04	0.04	0.10	0.12	0.48	0.56	0.82	0.87	0.98	0.99
Ohlson (1980) I	0.58	0.03	0.04	0.19	0.22	0.42	0.53	0.73	0.85	0.99	1.00
Ohlson (1980) II	0.57	0.07	0.10	0.25	0.31	0.43	0.55	0.64	0.76	0.93	0.96
Campbell et al. (2008) A I	0.56	0.03	0.03	0.16	0.27	0.42	0.53	0.73	0.85	1.00	1.00
Campbell et al. (2008) A II	0.59	0.07	0.08	0.23	0.35	0.39	0.56	0.64	0.77	0.93	0.96
Campbell et al. (2008) B I	0.57	0.04	0.04	0.22	0.30	0.44	0.54	0.68	0.79	0.98	0.97
Campbell et al. (2008) B II	0.57	0.10	0.14	0.25	0.36	0.44	0.55	0.61	0.73	0.86	0.89
Merton (1974) II	0.54	0.34	0.38	0.51	0.56	0.82	0.87	0.99	0.99	1.00	1.00

3.5 Empirical Results

3.5.1 Requests on Disclosed Company Information – Sample Level

For the purposes of this particular analysis, we used a sample of 269 bankrupt companies and five samples of 269 companies that, although financially distressed, remained solvent. Propensity score matching ensures that all samples exhibit comparable characteristics with regard to the likelihood of a company becoming bankrupt, the company's industry according to the SIC 1 classification, and the year of observation. Table 3.7 reveals that there are differences in the mean of the total weekly numbers of requests made to the EDGAR server between companies that went bankrupt and companies that, although financially distressed, remained solvent. Specifically, the table shows that significantly more requests were made for information on the companies that at the time were effectively, but not yet officially bankrupt than on the companies that remained solvent, despite their financial problems. In the case of requests that were made by specific market actors, these differences are particularly pronounced. This seems reasonable as a significant number of requests we identified came from professional investors. The same pattern emerges from the analysis of requests submitted from specific financial centers, which serve as proxies for professional investors. The relatively smaller difference that we observe across the entire period of interest, i.e., [–104, 26] weeks, may be attributed to a marked decline in the attention that investors pay to companies that have gone bankrupt immediately after bankruptcy has been declared.

Table 3.7: This table reports the total requests submitted by each group that we analyzed further. The requests are calculated as mean weekly requests for information submitted to the EDGAR server within a certain event window before and after a company's bankruptcy. The results indicate a higher level of requests for information on companies that will declare bankruptcy in the near future. This is more pronounced when we only consider the requests made by identified market actors.

	Mean of weekly total requests within [-52, -4] weeks before bankruptcy			Mean of weekly total requests within [-104, 26] weeks around bankruptcy		
	Bankrupt companies	Solvent companies	Δ(%)	Bankrupt companies	Solvent companies	Δ(%)
Total requests	549.034	492.969	11%	493.937	470.975	5%
Requests made by identified market actors	63.486	56.698	12%	56.207	51.614	9%
Requests made by financial centers	63.474	54.587	16%	56.435	51.901	9%

In the next step, we normalized and analyzed further our results on requests for information on comparable companies submitted to EDGAR during the period of interest. Table 3.15 in the Appendix 3.A reveals the time trend we observed in the patterns of requests submitted to EDGAR. For instance, to ensure that we can compare the attention that bankruptcy events received in 2004 to the attention they received in 2016, we have to take into account the time trend in the data. We define the aggregated requests in week (w) for information on company j that were submitted either from a specific group of investors g, such as investment banks or hedge funds or from one or more financial centers, as $Logs_{(g,j,w)}$. Company j is either a bankrupt company in set B or a matched company in set S. Each set includes 269 companies. The same index number, i.e., $b = s$, identifies each pair of one bankrupt and one matched solvent company. On that basis, we define $Attention_{(g,j,w)}$ in week w given to company j in the form of a request for relevant information to EDGAR from a certain group g as:

$$Attention_{(g,j,w)} = \frac{Logs_{(g,j,w)}}{\sum_{b=1}^{269} Logs_{(g,b,w)} + \sum_{s=1}^{269} Logs_{(g,s,w)}} \quad \text{with } j \in B \cup S \tag{9}$$

With respect to Equation 9 we measure the level of abnormal attention as the difference between the attention on bankrupt and matched companies from one sample divided by the attention on the matched companies from the same sample:

$$Abn.\ attention_{(g,w)} = \frac{\sum_{b=1}^{269} Attention_{(g,b,w)} - \sum_{s=1}^{269} Attention_{(g,s,w)}}{\sum_{s=1}^{269} Attention_{(g,s,w)}} \tag{10}$$

Equation 10 directly calculates the percentage level of abnormal attention that bankrupt companies receive weekly compared to the attention that their solvent matches receive. Figure 3.4 illustrates the level of abnormal attention that companies in the bankrupt category receive as this is reflected in (a) the number of total requests for relevant information submitted to EDGAR, (b) the number of all such requests submitted by identified market actors, and (c) the number of all such requests submitted to EDGAR from within specific financial centers.

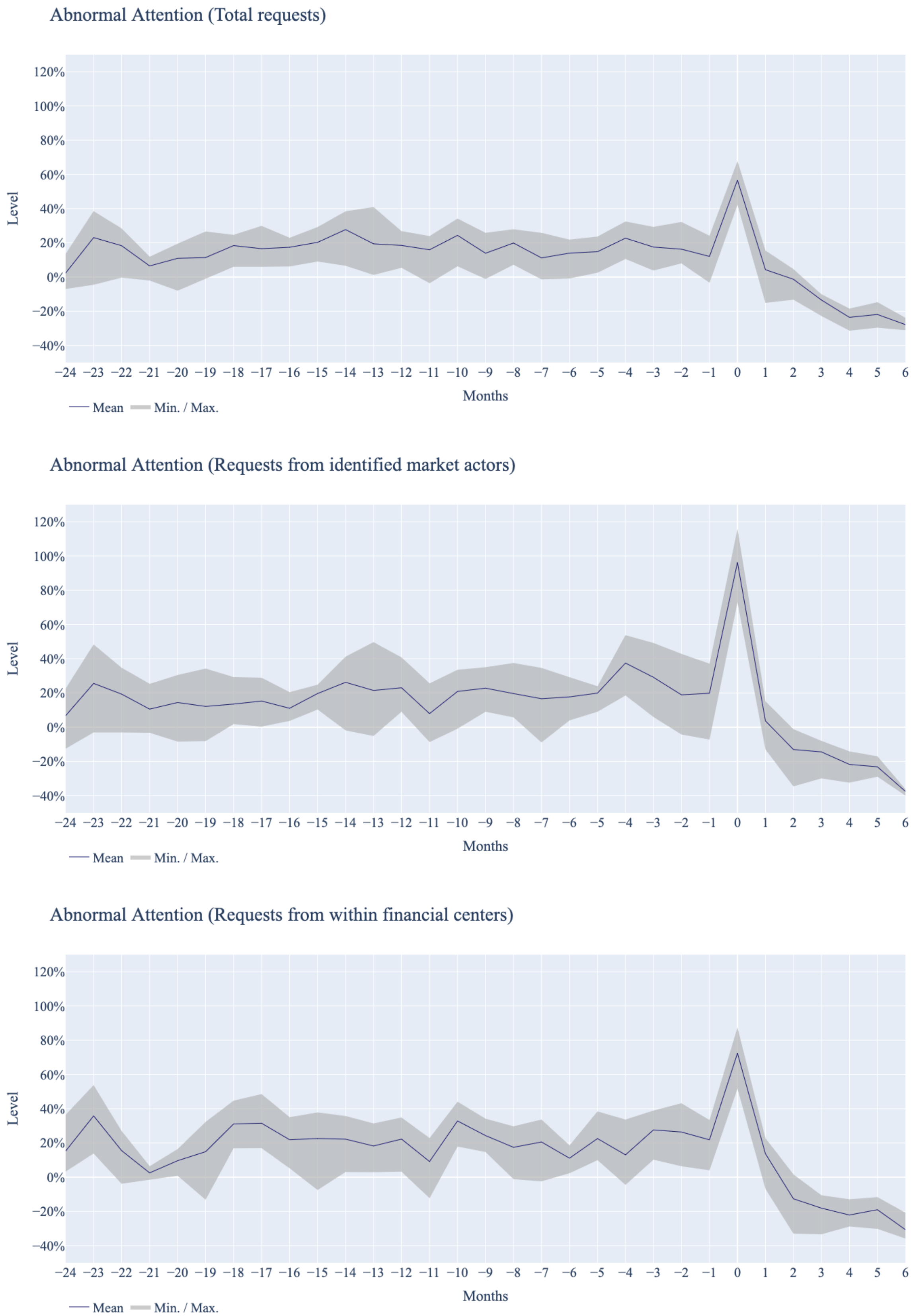


Figure 3.4: The three plots included in this figure illustrate the percentage level of abnormal attention paid to bankrupt companies, measured according to Equation 10. The abnormal attention is plotted with regard to (1) the total requests submitted to the EDGAR server, (2) the requests made by all identified market actors, and (3) the requests made from within all identified financial centers over a period spanning 24 months before and six months after bankruptcy. The grey area spans the minimum and maximum values for any of the five samples of matched companies that, although financially distressed, remain solvent. The blue line represents the mean percentage level of abnormal attention, based on these five samples.

Figure 3.4 shows the mean, minimum, and maximum values of the percentage levels of abnormal attention that we calculated on the basis of the five matched samples. The analysis of these patterns reveals that the number of requests for the filings of companies that were effectively, but not yet officially bankrupt at the time increased in the 18–20 months before bankruptcy and exceeds the number of requests made during the same period for the filings of companies that, although financially distressed, remained solvent. In other words, our results show that at least in the 18 months before a company declares bankruptcy, the attention it receives from investors is almost constantly higher than that its match receives in the same period. In Table 3.8 we use weekly aggregations and in Table 3.9 we use monthly aggregations of filing requests to show the mean percentage levels of abnormal attention the companies in the bankrupt category received in different periods before and after they became bankrupt.

The t-tests we applied reveal that the stated mean percentage levels of abnormal attention differ significantly from zero (see Tables 3.8 and 3.9). We calculated the means on a weekly and monthly aggregation level to verify that the results are not affected by the time-based aggregation of the measure we used to capture abnormal attention. Furthermore, we explicitly excluded from our calculations data collected during the two weeks before and the two weeks after bankruptcy (or one month before and one month after bankruptcy, respectively).

Table 3.8: This table reports the t-statistics and corresponding p-values and the mean percentage levels of abnormal attention, as reflected in (a) the total number of requests, (b) the requests made by identified market actors, and (c) the requests made from identified financial centers in a specified period. The calculations are based on weekly aggregations of the abnormal attention measure. We explicitly exclude the two weeks before and after the bankruptcy event in each period.

Abn. attention$_{(g,w)}$	Period (weeks; 0 = bankruptcy)	t-statistic	p-value	Mean abnormal attention
	Bankrupt sample vs matched samples			
Total requests	[-104, -53]	10.6176	0.0000	0.1653
	[-52, -4]	10.9102	0.0000	0.1643
	[3, 26]	-6.7399	0.0000	-0.1615
Requests from identified market actors	[-104, -53]	8.7656	0.0000	0.1671
	[-52, -4]	11.3554	0.0000	0.2158
	[3, 26]	-6.6072	0.0000	-0.1837
Requests from financial centers	[-104, -53]	10.0655	0.0000	0.2016
	[-52, -4]	12.2761	0.0000	0.2165
	[3, 26]	-7.5384	0.0000	-0.1704
	Matched samples vs placebo samples			
Total requests	[-104, 26]	-0.6556	0.5126	-0.0090
Requests from identified market actors	[-104, 26]	0.1048	0.9167	0.0056
Requests from financial centers	[-104, 26]	0.6489	0.5170	0.0163

Tables 3.8 and 3.9 show that time aggregation causes no systematic effects. The same tables show that the companies that eventually went bankrupt received much more abnormal attention from identified market actors in the period of [–52, –4] weeks (or [–12, –1] months, respectively) before bankruptcy. Within this period, companies that eventually declare bankruptcy receive between 14.9% and 21.6% more attention than their peer companies that remained solvent thereafter (p-values < 0.01). The results reveal a similar difference in the attention that these two categories of companies received in the period of [–104, –53] weeks (or [–24, –13] months, respectively) before the companies in the first category declared bankruptcy. After the bankruptcy event the number of requests for the filings of the companies that have gone bankrupt drops below the number of requests for the filings of their peer companies that remained solvent, despite their financial troubles.

Table 3.9: This table reports the t-statistics and corresponding p-values and the mean percentage levels of abnormal attention, as reflected in (a) the total number of requests, (b) the requests made by identified actors, and (c) the requests made from identified financial centers in a specified period. The calculations are based on a monthly aggregation of the abnormal attention measure. We explicitly exclude the month before and after the bankruptcy event.

Abn. attention$_{(g,m)}$	Period (months; 0 = bankruptcy)	t-Statistic	p-Value	Mean abnormal attention
	Bankrupt vs matched samples			
Total requests	[-24, -13]	7.3550	0.0000	0.1378
	[-12, -1]	10.1446	0.0000	0.1490
	[1, 6]	-3.0363	0.0103	-0.1619
Requests from identified market actors	[-24, -13]	6.3852	0.0000	0.1257
	[-12, -1]	1.2114	0.0000	0.1763
	[1, 6]	-3.6567	0.0033	-0.2297
Requests from financial centers	[-24, -13]	4.7611	0.0001	0.1572
	[-12, -1]	7.5297	0.0000	0.1776
	[1, 6]	-4.0555	0.0016	-0.1802
	Matched vs placebo samples			
Total requests	[-24, 6]	-0.4237	0.6732	-0.0132
Requests from identified market actors	[-24, 6]	0.2133	0.8318	0.0109
Requests from financial centers	[-24, 6]	0.4859	0.6288	0.0189

We used the placebo samples to further validate the results on the abnormal attention financially distressed companies receive before they declare bankruptcy. Figure 3.5 illustrates the levels of abnormal attention companies received, calculated as a percentage of the total requests for relevant information submitted to the EDGAR server during the period of interest and based on the five matched samples and the respective five placebo samples. As Figure 3.5 shows, the peer companies that remained solvent and the placebo companies do not differ in terms of the attention they received during the period our study covers. Repeating the same analysis for requests submitted by the market actors we identified and from specific financial centers yields similar patterns that also exhibit no abnormal levels of attention paid to those companies.

The exact percentage levels of abnormal attention are reported in tables 3.8 and 3.9. As Figure 3.5 indicates no obvious structural break in the percentage level of abnormal attention, we conducted the t-tests on the mean percentage levels of abnormal attention companies received on a monthly and weekly basis for the entire observation period of [–104, 26] weeks (or [–24, 6] months, respectively). The t-tests show that the percentage level of abnormal attention does not differ significantly from zero (p-values > 0.5) and the companies in the respective samples received no abnormal attention, regardless of the period the aggregated data cover.

The higher demand for information on companies that are effectively, though not yet officially, bankrupt that our results document indicates that market actors anticipate imminent bankruptcies at an early stage. Comparing figures 3.4 and 3.5 provides intuitive empirical evidence that disclosed company information is indeed relevant to investors, as it can help predict corporate bankruptcies. The levels of abnormal attention that market actors pay to companies that eventually declare bankruptcy confirm that such actors clearly try to gather more information on such companies than on similar companies that, although financially distressed, remain solvent.

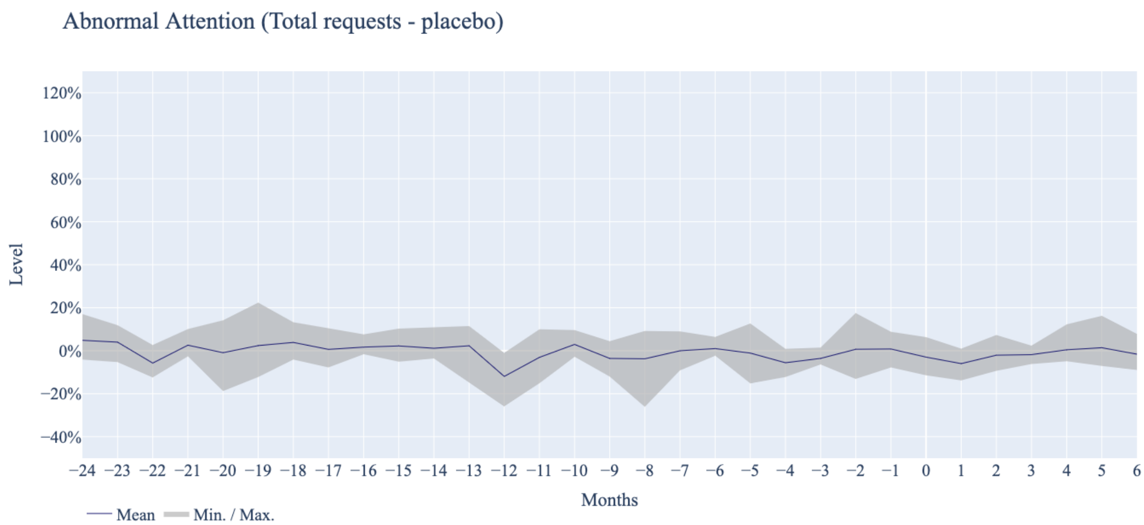


Figure 3.5: This figure illustrates the percentage level of abnormal attention, based on the total requests for information on the samples of matched companies, compared to the corresponding samples of placebo companies. The abnormal attention is plotted over a period spanning 24 months before and six months after bankruptcy. The grey area spans the minimum and maximum values in these comparisons and the blue line represents the mean percentage level of abnormal attention, based on these comparisons.

3.5.2 Explaining Differences in Requests for Disclosed Company Information

To gain more insight into why investors pay more attention to financially distressed companies that eventually go bankrupt and companies that, although financially distressed, remain solvent, we examined how specific groups of market actors behave with regard to the research they conduct on the EDGAR server. In Equation 11, we perform OLS regressions with a constant and a time variable that captures the number of weeks our observations cover. The dependent variables are the standardized absolute number of weekly requests submitted to EDGAR by different groups of market actors for filings of companies that were effectively, but not officially bankrupt at the time. Standardizing absolute numbers of weekly requests enables us to compare the results we obtained for different groups of market actors and to refine the interpretation of the patterns we observe in the requests these groups of market actors made before and after the distressed companies declared bankruptcy.

$$z\left(\sum_{b=1}^{269} Logs_{(g,b,w)}\right) \sim \alpha + \beta_1 Time_w + \epsilon \tag{11}$$

Table 3.10 displays the results we obtained from the OLS regressions. These results show that investment banks and hedge funds requested significantly more publicly available information on companies that were effectively bankrupt but had not yet declared bankruptcy. Asset management companies also requested more such information within the period of [–104, –53] weeks. These results are in line with the results we present in Section 3.5.1 and confirm that investors pay abnormally high levels of attention to effectively bankrupt companies before these go formally bankrupt. As Table 3.1 shows, these three categories account for the majority of market actors and therefore for the highest proportion of the requests made to EDGAR for the filings of such companies, driving the pattern we observe.

At the same time, we observe a negative time trend in the attention these three groups of investors pay to effectively bankrupt companies before bankruptcy. In other words, investors in these three groups request less information on the companies that are approaching formal bankruptcy. To interpret this rather counter-intuitive observation, we need to take a closer look at the holdings of bankrupt companies these investors have (see Figure 3.8). Professional investors start selling their holdings of companies that will declare bankruptcy in the foreseeable future 11–14 months before the bankruptcy event (we discuss this behavior in more detail in Section 3.5.4). Once investors have started reducing their holdings in a company, it is understandable that their interest in that company will naturally decrease and they will therefore make fewer requests for relevant information. Moreover, in contrast to non-investors, professional investors reduce their requests for information on a company that has declared bankruptcy. Following the hypothesis that Grossman and Stiglitz (1980) put forward—namely, that information gathering and processing are costly to investors—the behavior we observe is plausible.

Table 3.10: This table shows the results we obtained from the OLS regressions (Equation 11). The dependent variable in each regression is the number of standardized absolute weekly requests submitted to EDGAR by a certain group of market actors for the filings of effectively bankrupt companies. We repeated the OLS regressions for different periods before and after each company's bankruptcy to show that the attention different market actors pay to these companies is heterogeneous. The independent variable *Time* reflects the number of the observation weeks and starts with 1 for each period, while ***, **, * denote statistical significance at the 1%, 5%, and 10% level. respectively.

Periods (weeks; 0 = bankruptcy)			[-104, -53]	[-52, -4]	[-104, -4]	[2, 26]
Asset management companies	α	β_0	0.5945**	-0.3863*	0.2790	-0.9796**
		p-Value	0.0240	0.0711	0.1042	0.0369
	Time	β_1	-0.0200**	0.0059	-0.0071**	0.1017***
		p-Value	0.0248	0.4460	0.0180	0.0038
Hedge funds	α	β_0	1.0151***	-0.0663	0.9757***	-0.6512***
		p-Value	0.0049	0.6503	0.0000	0.0000
	Time	β_1	-0.0169	-0.0089	-0.0163***	0.0065
		p-Value	0.1534	0.1003	0.0000	0.4456
Investment banks	α	β_0	0.1284	0.7380***	0.6929***	-1.0485***
		p-Value	0.5559	0.0001	0.0000	0.0000
	Time	β_1	0.0156**	-0.0284***	-0.0078***	-0.0234*
		p-Value	0.0375	0.0000	0.0044	0.0707
Banks	α	β_0	-0.0102	-0.0625	-0.1397	-0.9632***
		p-Value	0.9631	0.7835	0.3801	0.0004
	Time	β_1	0.0018	0.0162*	0.0063**	-0.0080
		p-Value	0.8109	0.0568	0.0254	0.6367
Law firms	α	β_0	-0.7780***	-0.6531***	-1.1564***	0.5900**
		p-Value	0.0000	0.0000	0.0000	0.0198
	Time	β_1	0.0051	0.0407***	0.0195***	-0.0408**
		p-Value	0.2176	0.0000	0.0000	0.0237
News agencies	α	β_0	-0.8502***	-0.6266***	-0.9293***	0.0951
		p-Value	0.0000	0.0096	0.0000	0.7721
	Time	β_1	0.0112*	0.0261***	0.0127***	0.0700***
		p-Value	0.0680	0.0035	0.0000	0.0061
Terminal providers	α	β_0	-0.8549***	0.0748	-1.0128***	0.9860**
		p-Value	0.0000	0.8147	0.0000	0.0217
	Time	β_1	0.0102***	0.0148	0.0183***	-0.0587*
		p-Value	0.0088	0.2102	0.0000	0.0518
Data providers	α	β_0	-0.8349***	0.1453	-1.3152***	0.4807*
		p-value	0.0000	0.6042	0.0000	0.0598
	Time	β_1	0.0006	0.0207**	0.0241***	-0.0275
		p-value	0.4732	0.0485	0.0000	0.1259

Beside the abnormally high levels of attention that professional investors pay to companies that eventually go bankrupt, our results also show that news agencies and law firms request less information on effectively bankrupt companies before the bankruptcy event. However, in the case of these two groups, the pattern of search behavior exhibits a positive time trend. After a company has declared bankruptcy, news agencies and law firms increase their requests on the filings of the now bankrupt company. This observation seems plausible, considering that corporate bankruptcies generate media attention and that law firms are frequently consulted when a company goes bankrupt. Moreover, these groups of market actors may well need to look for updated information on a bankrupt company via terminal providers such as Bloomberg and Reuters and data providers such as CapitalIQ. These largely intuitive secondary results complete the overall picture and substantiate the validity of our findings, the research methodology, and the quality of our data.

3.5.3 Plausibility Check and Alternative Explanations

In this section we check the plausibility of our results on the abnormal levels of attention that certain investors pay to companies before these go bankrupt. For this purpose, we adjust and apply the estimated bankruptcy prediction models that Altman (1968), Ohlson (1980), and Campbell et al. (2008) introduced. We have already used these models to validate the matched samples in Section 3.4.3. If the difference between the requests that certain investor groups make for the filings of companies that eventually go bankrupt and for those that remain solvent is statistically significant, the data on such requests could help differentiate between these two categories of companies while their future is still unclear. In other words, such data could help predict whether a company is likely to go bankrupt or to overcome its financial difficulties.

Table 3.11 shows the AUC values of the four different bankruptcy prediction models we apply here. These values are based on observations corresponding to periods I (out-of-sample) and II (in-sample). We obtained the AUC values by applying the estimated bankruptcy prediction models with fixed coefficients to all 269 bankrupt companies and all 269 companies in one of the four matched samples. More precisely, we used as an additional explanatory variable the logarithmic number of total requests $ln(\sum_{m=-12}^{m=-1} Logs_{(j,m)})$ made for company $j \in B \cup S$ in the period of [–12, −1] months before that company became bankrupt, fixing the coefficients for all of the remaining independent variables used in a specific model.

The results in the first column of Table 3.11 are close to 0.5 and indicate that the estimated bankruptcy prediction models fail to differentiate effectively between bankrupt companies and their solvent matches. The AUC values we obtained when we applied the extended models, which include the logarithmic number of total requests made in the period of [–12, −1] months before bankruptcy as an additional independent variable, are displayed in the second column of

Table 11. The inclusion of this variable appears to increase the accuracy with which a model predicts bankruptcy. Adding the logarithmic number of total requests increases the AUC values by 16.07% (minimum 9.84%, maximum 25.42%) on average. If we include in the measure that captures investor attention the logarithmic number of requests made by identified market actors within the period of [–12, –1] months before a company's bankruptcy, the AUC values increase on average by 20.51% (minimum 15.52%, maximum 31.03%). Repeating the analysis for the logarithmic number of requests made from specific financial centers, increases the AUC values by 16.32% (minimum 8.20%, maximum 22.41%) on average.

Table 3.11: This table displays the AUC values of four different bankruptcy prediction models, based on observations covering periods I and II. We obtained the AUC values by applying the estimated bankruptcy prediction models with fixed coefficients and with or without the logarithmic number of total requests to differentiate between bankrupt and matched companies and between matched and placebo companies. To estimate the coefficients, we followed the approach described in Appendix 3.B.

	Matched samples		Placebo samples	
	AUC (estimation without attention)	AUC (estimation with attention	AUC (estimation without attention)	AUC (estimation with attention)
Altman (1968) I	0.57	0.65	0.54	0.59
Altman (1968) II	0.58	0.65	0.56	0.60
Ohlson (1980) I	0.61	0.67	0.58	0.65
Ohlson (1980) II	0.60	0.66	0.57	0.64
Campbell et al. (2008) A I	0.59	0.74	0.60	0.62
Campbell et al. (2008) A II	0.58	0.72	0.59	0.62
Campbell et al. (2008) B I	0.64	0.74	0.57	0.59
Campbell et al. (2008) B II	0.63	0.74	0.57	0.59

We performed the same analysis using data on the corresponding placebo companies. The AUC values from these tests are displayed in columns 3 and 4 of Table 3.11. The results indicate that the logarithmic number of total requests increases a model's discriminatory power only marginally, failing to differentiate adequately between the solvent matches of the bankrupt companies and the corresponding placebo companies. Repeating the analysis with the logarithmic number of requests submitted by identified market actors or from within specific financial centers produces similar AUC values.

Overall, using AUC values as a validity measure indicates that taking into account the logarithmic number of total requests as a measure of attention paid to companies makes it possible to differentiate more accurately between companies that are effectively bankrupt and companies that are likely to remain solvent, despite their financial problems. In contrast, bankruptcy prediction models that rely only on accounting-based and market-based independent variables cannot differentiate adequately between these two categories of companies.

We also examined whether there might be other explanations for the differences we observed between companies that eventually go bankrupt and companies that, although financially distressed, remain solvent in terms of the attention they receive from investors. More precisely, we checked whether any key company characteristics, including ownership structure, or whether particular aspects of the market structure might attract more attention to companies that eventually go bankrupt. In Equation 12, we measure the dependent variable $\Delta(Logs)$ in each of the five regressions we run as the difference between bankrupt companies and their solvent matches in the logarithmic number of total requests for relevant information investors submit. For these regressions, we used data covering the period of [–12, –1] months before the companies in the first category went bankrupt. To measure the independent variables, we used the most recent annual data available before the date on which a company declared bankruptcy. We calculated market variables, such as buy-and-hold stock return and stock return volatility, using the most recent data to the end of the respective fiscal year, excluding, however the last month preceding bankruptcy. Table 3.12 presents the results of diff-in-diff OLS regressions according to Equation 13. We ran diff-in-diff OLS regressions to test alternative independent variables that might explain the difference that we observe when we analyze the total number of requests made to the EDGAR server.

$$\Delta(Logs) = ln\left(\sum_{m=-12}^{m=-1} Logs_{(b,m)}\right) - ln\left(\sum_{m=-12}^{m=-1} Logs_{(s,m)}\right) \quad \text{for } b = s \tag{12}$$

$$\Delta(Logs) \sim \alpha + \sum_{v=1}^{n} \beta_v \left(x_{(v,b)} - x_{(v,s)}\right) + \epsilon \quad \text{for } b = s \tag{13}$$

Although the difference in the logarithmic number of a company's filings and the difference in the stock liquidity between bankrupt companies and their solvent matches have a statistically significant effect on the difference in the logarithmic number of total requests between bankrupt companies and their solvent matches, their effect is too small to explain it as the R^2 values and the adjusted R^2 values appears to be very small. We additionally checked the validity of our results by measuring the dependent variable $\Delta(Logs)$ in each of the five regressions in two further ways. First, we checked the difference between the logarithmic requests identified market actors made for information on companies that eventually went bankrupt and those made for companies that remained solvent. Second, we also checked the difference between the logarithmic number of requests made for information on the first category of companies and those made for the second category from the 30 financial centers we identified (unreported results). However, using different measures to capture the dependent variable $\Delta(Logs)$ did not lead to any substantial change in the results.

Table 3.12: This table displays the diff-in-diff OLS regression results showing the relation between specific independent variables and the observed differences between requests for information on effectively bankrupt companies and requests for information on matched companies in the period of [–12, –1] months before bankruptcy. Columns 1–5 list the results based on the five matched samples and the respective bankruptcy prediction models. The dependent variable $\Delta(Logs)$ in each of the five regressions is the difference in the logarithmic number of total requests (Equation 12), while ***, **, * denote statistical significance at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)
	Altman (1968)	Ohlson (1980)	Campbell et al. (2008) A	Campbell et al. (2008) B	Merton (1974)
Dependent variable			Δ(Logs)		
Intercept	0.0111	0.0055	0.0039	0.0028	0.0137
	(0.2735)	(0.5713)	(0.7017)	(0.7774)	(0.1648)
Δ ln(Company size$_a$)	0.0157**	-0.0147*	0.0060	0.0014	0.0065
	(0.0167)	(0.0569)	(0.4521)	(0.8676)	(0.3757)
Δ Leverage$_a$	0.0019	0.0328	-0.0647	0.0206	-0.0283
	(0.9666)	(0.7109)	(0.3544)	(0.6205)	(0.3447)
Δ ROA$_a$	0.0352	0.0959*	-0.0137	0.0241	-0.0106
	(0.6854)	(0.0728)	(0.7860)	(0.6533)	(0.7978)
Δ ln(Analysts)$_a$	0.0044	0.0059	-0.0033	-0.0106	0.0130
	(0.6991)	(0.6217)	(0.7765)	(0.3993)	(0.2943)
Δ ln(Company age$_a$)	0.0107	0.0056	0.0061	0.0150**	0.0095
	(0.1518)	(0.3948)	(0.4216)	(0.0457)	(0.1942)
Δ CapEx$_a$	-0.0678	-0.0747	-0.0389	0.0220	-0.2120
	(0.6692)	(0.5872)	(0.7705)	(0.8727)	(0.1552)
Δ R&D$_a$	0.1874*	0.1439*	-0.0196	0.0017	0.0630
	(0.0761)	(0.0912)	(0.8078)	(0.9868)	(0.4229)
Δ Intangibles$_a$	-0.0206	-0.0247	0.0004	-0.0155	-0.0338
	(0.6177)	(0.4829)	(0.9901)	(0.6834)	(0.3495)
Δ Tobin's Q$_a$	0.0017	-0.0206***	0.0001	-0.0020	-0.0020
	(0.8773)	(0.0089)	(0.9884)	(0.8426)	(0.8139)
Δ Amihud$_a$	-1.1809**	-1.5761***	-1.4691**	-1.6635***	-1.5177***
	(0.0421)	(0.0047)	(0.0115)	(0.0085)	(0.0073)
Δ B&h stock return$_a$	-0.0081	-0.0250*	-0.0125	-0.0034	-0.0150
	(0.6007)	(0.0672)	(0.4043)	(0.8414)	(0.3182)
Δ Stock return vola.$_a$	0.0516*	0.0295	-0.0152	0.0289	0.0827
	(0.0850)	(0.3069)	(0.6221)	(0.3794)	(0.1868)
Δ ln(No. filings$_a$)	0.0768***	0.0945***	0.0588***	0.0850***	0.0912***
	(0.0000)	(0.0000)	(0.0044)	(0.0000)	(0.0000)
Δ Active ownership$_a$	0.0869***	0.0143	0.0375	0.0256	0.0919***
	(0.0008)	(0.5569)	(0.1526)	(0.3346)	(0.0009)
Δ Complicated company$_a$	-0.0036	-0.0254	0.0157	0.0334	-0.0158
	(0.8880)	(0.2361)	(0.5090)	(0.1562)	(0.5259)
Observations	269	269	269	269	269
R^2	0.265	0.207	0.097	0.152	0.217
Adj. R^2	0.221	0.160	0.043	0.102	0.170

With regard to a shorter time horizon, the change in company-specific conditions on the capital market might also explain the difference between effectively bankrupt companies and their solvent matches in terms of the attention they received from investors. In particular, we see that the differences in buy-and-hold stock returns and in stock-return volatility between bankrupt companies and their solvent matches change over time in a way that could explain the higher number of requests on disclosed company information on the first category of companies. These differences are presented in Figure 3.6.

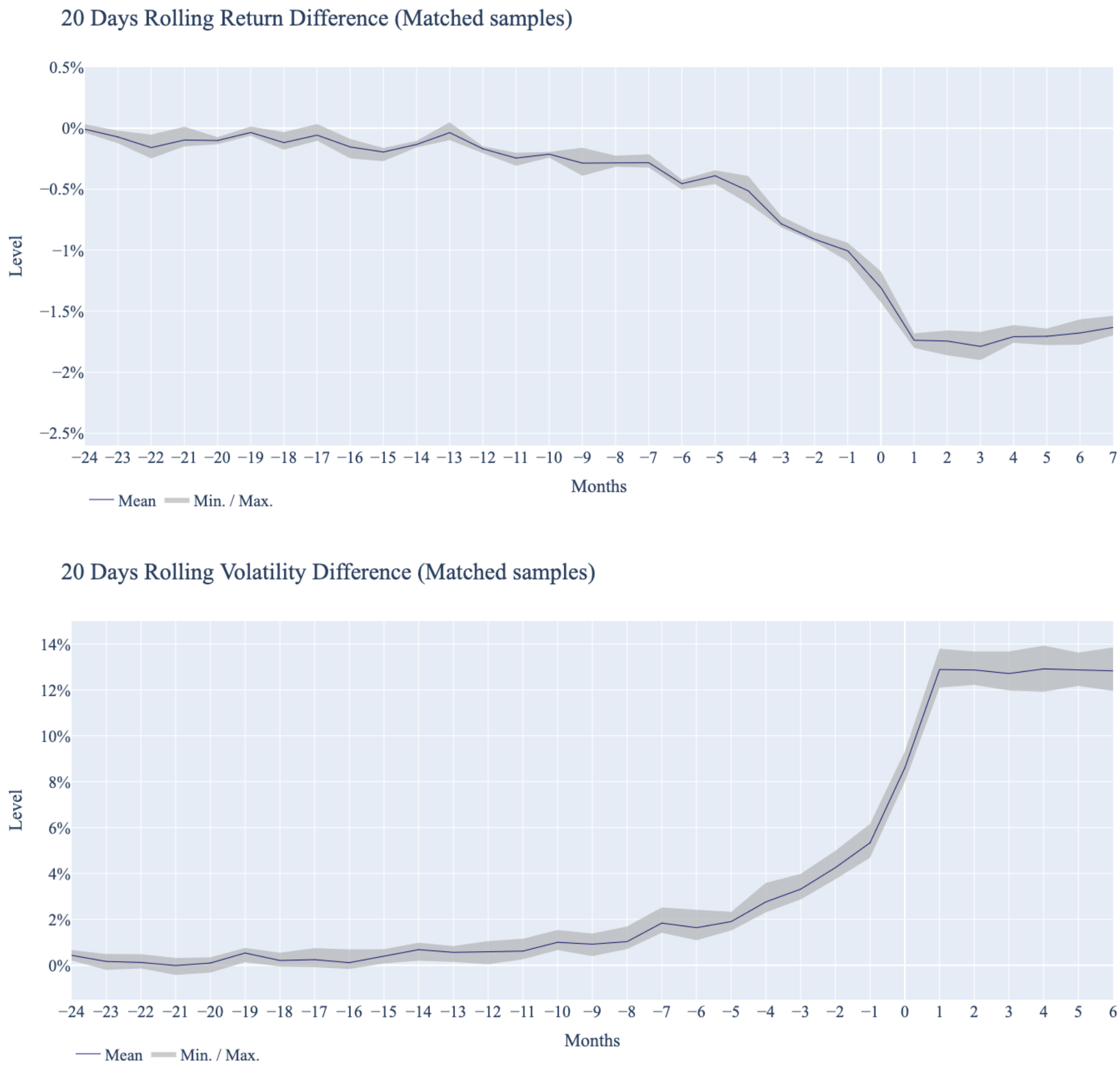
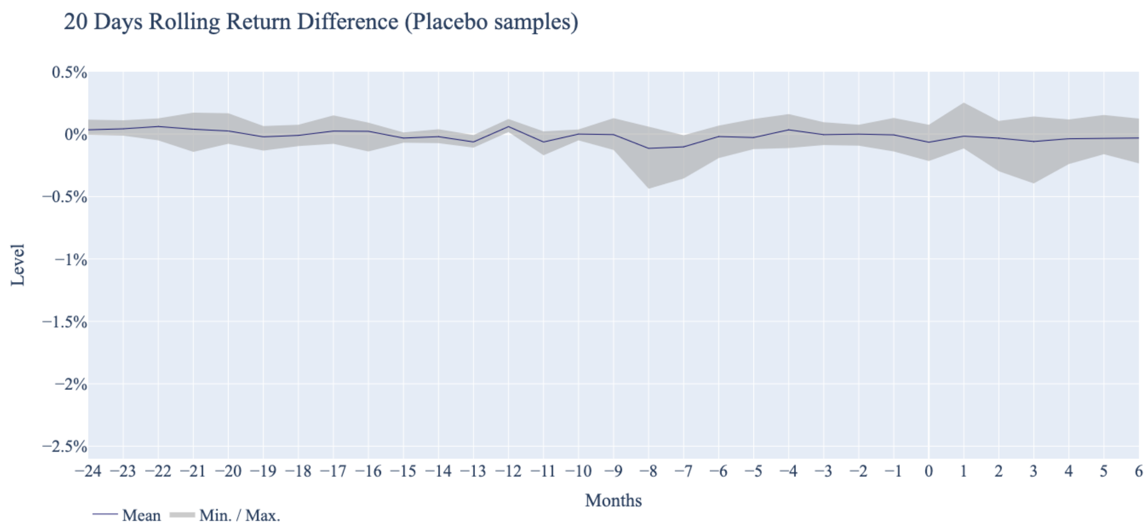


Figure 3.6: The plots depict the mean differences in 20 days' rolling buy-and-hold stock return and 20 days' rolling stock return volatility, derived from 269 pairs of bankrupt and matched companies. The plots cover a period of 24 months before and six months after bankruptcy. The grey area spans the minimum and maximum mean differences between the bankrupt sample and any of the five matched samples. The blue line represents the mean differences of 20 days' rolling buy-and-hold stock return and 20 days' rolling stock return volatility on the basis of the pairs we derived from these five samples.

As the figure shows, the stock-return volatility of effectively bankrupt companies increases, while the buy-and-hold stock return decreases more than in the case of their matched companies. However, we also note that the differences in buy-and-hold stock return and in stock-return volatility between the two groups of companies start to expand 12 months before bankruptcy. As we have already shown that the number of requests for the filings of effectively bankrupt companies starts increasing 18–20 months before bankruptcy, it is unlikely that buy-and-hold stock return and stock-return volatility lead to the differences we note here.

Stock prices reflect, at least in part, the total amount of information on companies that investors request and process in a particular period (Verrecchia, 1982). Our results show plausible changes in the buy-and-hold stock returns and in stock-return volatility ahead of a company's bankruptcy. These changes are in line with economic theory and reveal how investors process relevant information and how their actions are, in turn, translated into changes in the stock prices of the respective company. Overall, our analysis indicates that investors pay abnormally high levels of attention to companies that eventually go bankrupt before the market reacts to the changes in these companies' financial status. This finding provides tentative evidence that unusually high levels of attention paid to a financially distressed company could help predict decreases in buy-and-hold return and increases in the stock-return volatility.

To further validate the differences we observe between companies that eventually went bankrupt and their solvent matches in terms of buy-and-hold stock return and stock-return volatility, we ran additional tests using the samples of solvent matches and the corresponding placebo samples. Figure 3.7 shows that there are no structural differences in the buy-and-hold stock return and in stock-return volatility between these samples. Again, this result seems plausible, given that we did not detect any structural difference between the companies that were financially distressed but remained solvent and the corresponding companies in the placebo samples.



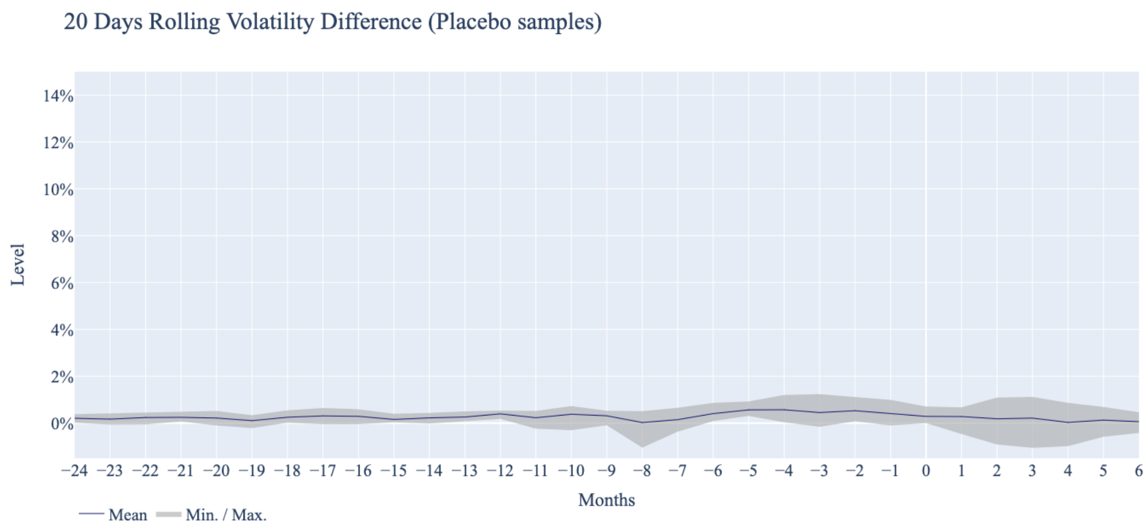


Figure 3.7: The plots display the mean differences in 20 days' rolling buy-and-hold stock return and 20 days' rolling stock return volatility, derived from 269 pairs of matched and placebo companies. The plots span a period of 24 months before and six months after bankruptcy. The grey area spans the minimum and maximum mean differences between any of the five matched samples and the five corresponding placebo samples. The blue line represents the mean differences of 20 days' rolling buy-and-hold stock return and 20 days' rolling stock return volatility on the basis of the pairs we derived from these five samples.

3.5.4 Requests for Disclosed Company Information on the Investor–Company Level

The analysis we have presented in the previous sections is based on the aggregated data we collected on samples of bankrupt companies and of matching companies that remained solvent. To substantiate this analysis, we ran further tests on the investor–company level. On that basis, we were able to investigate in more detail whether, first, imminent bankruptcy explains why professional investors pay more attention to a financially distressed company and, second, whether the degree of attention investors pay to a financially distressed company helps predict a reduction in these investors' holdings of that company. For that purpose, we used data on Form 13F filings and constructed a panel of quarterly observations on the holdings that professional investors had in the companies that went bankrupt and their solvent matches. For the controls, we used data from the EDGAR log files on the requests for information on those companies that investors had submitted to the server, company data derived from the Compustat database and stock-performance data derived from the CRSP database. The individual investors we identified are either investment banks, hedge funds, or asset management companies. Each investor we included had to hold shares in any of the 269 bankrupt companies or any of the 853 solvent companies contained in at least one of the five matched samples. We excluded all observations within the period of [-1, $+\infty$] quarters before and after bankruptcy.

The first regression analysis we ran using these data is presented in Table 3.13 and reveals the degree of attention that an individual professional investor paid to a specific company in a specific quarter during the period of interest. We define the $Share\ of\ attention_{(i,j,q)}$ in Equation 14 as the ratio of all requests that a specific professional investor $i \in g$ has made for information on a specific company $j \in B \cup S$ in a certain quarter q to the total number of requests for information that this specific investor i submitted to EDGAR in the same quarter. The set of companies whose filings are stored on EDGAR is denoted by J and comprises the subsets B and S ($(B \cup S) \subset J$). The $Share\ of\ attention_{(i,j,q)}$ reflects the fact that attention is a limited resource (Kahneman, 1973).

$$1 Share\ of\ attention_{(i,j,q)} = \frac{Logs_{(i,j,q)}}{\sum_{n=1}^{J} Logs_{(i,n,q)}} \quad \text{with } j \in g \text{ and } j \in B \cup S \tag{14}$$

To estimate each regression, we used a lead-lag structure with regard to the dependent variable setting it at one quarter ahead ($q + 1$). All regressions take into account year fixed effects. Table 13 also shows the regression results for company fixed effects in Column 1, industry fixed effects in columns 2 and 4, investor fixed effects in columns 3–5 and year $\times$ industry fixed effects in column 5. We ran these additional tests to ensure that the regression results are not driven by unobserved effects. We estimated all regressions with standard errors clustered at the company level. To check the robustness of the analysis, we re-estimated all regressions, using standard errors clustered at the industry level. The results confirm that our analysis is robust.

The baseline regression is displayed in Column 1 of Table 3.13. As bankruptcy is a fixed company effect in our setting, we did not include the dummy variable $d(Bankrupt_{(j)})$ in Regression 1 when we controlled for fixed company effects. The results show that company size and investor ownership significantly increase the share of attention and company age significantly decreases the share of attention in the subsequent quarter. These relationships can be observed in every regression. When we take into account investor fixed effects, the controls for investor size, investor ownership, and the number of investor holdings are no longer significant. If we omit fixed company effects, the coefficient of the bankruptcy dummy is positive and statistically significant at the 1% level (p-value < 0.001 in Column 2) when we control for year and industry fixed effects, or positive and statistically significant at the 5% level (p-values < 0.05, columns 3–5) on all other specifications of the fixed effects. This result is consistent with the results we report in section 3.5.1 and 3.5.2 and supports the empirical evidence that professional investors gather more information on companies that are effectively, though not yet officially, bankrupt. This result is robust when we control for investor fixed effects.

Table 3.13: This table shows the results of the OLS regressions where the dependent variable is *Share of attention*$_{(i,j,q+1)}$. The independent variables include company and investor characteristics (Appendix 3.D). We excluded observations within the period of [-1, $+\infty$] quarters before and after bankruptcy. All specifications include year fixed effects. We also include company fixed effects in column 1, industry fixed effects based on the SIC 1 industry classification in column 2, investor fixed effects in column 3, industry and investor fixed effects in column 4 and investor and year $\times$ industry fixed effects in column 5. All standard errors are clustered by company. We report the p-values in parentheses; ***, **, * denote statistical significance at the 1%, 5%, and 10% level respectively.

	Pre-bankruptcy window				
	(1)	(2)	(3)	(4)	(5)
Dependent variable	Share of attention$_{(i,j,q+1)}$				
Intercept	1.6304***	1.5849***	0.0226	0.0355	0.0282
	(0.0000)	(0.0000)	(0.9482)	(0.9185)	(0.9347)
ln(**Company size**$_{(j,a)}$)	0.0163**	0.0249***	0.0272***	0.0223***	0.0223***
	(0.0245)	(0.0035)	(0.0000)	(0.0000)	(0.0000)
Leverage$_{(j,a)}$	-0.0085**	-0.0112	-0.0121***	-0.0083***	-0.0083***
	(0.0269)	(0.2230)	(0.0019)	(0.0093)	(0.0093)
ROA$_{(j,a)}$	0.0114	-0.0358**	-0.0240**	-0.0125	-0.0125
	(0.5375)	(0.0297)	(0.0423)	(0.3056)	(0.3056)
ln(**Analysts**)$_{(j,a)}$	0.0025	-0.0209*	-0.0160***	-0.0139***	-0.0139***
	(0.6828)	(0.0894)	(0.0007)	(0.0018)	(0.0018)
ln(**Company age**$_{(j,a)}$)	-0.0393***	-0.0117*	-0.0071**	-0.0092***	-0.0092***
	(0.0072)	(0.0783)	(0.0299)	(0.0076)	(0.0076)
CapEx$_{(j,a)}$	0.0431	0.0329**	0.0022	0.0278	0.0278
	(0.1647)	(0.0274)	(0.9176)	(0.1604)	(0.1604)
R&D$_{(j,a)}$	0.0641*	0.0446	0.0591**	0.0544*	0.0544*
	(0.0896)	(0.3285)	(0.0193)	(0.0524)	(0.0524)
Intangibles$_{(j,a)}$	-0.0074	0.0038	0.0021	0.0053	0.0053
	(0.8344)	(0.8437)	(0.8717)	(0.7048)	(0.7048)
Tobin's Q$_{(j,a)}$	0.0029**	0.0022	0.0031***	0.0021***	0.0021***
	(0.0118)	(0.2280)	(0.0010)	(0.0100)	(0.0100)
Amihud$_{(j,a)}$	0.4583	0.6286*	0.6726***	0.4751*	0.4751*
	(0.2642)	(0.0504)	(0.0070)	(0.0525)	(0.0525)
B&h stock return$_{(j,a)}$	-0.0027	0.0005	-0.0008	0.0001	0.0001
	(0.4028)	(0.9082)	(0.8019)	(0.9837)	(0.9837)
Stock return vola.$_{(j,a)}$	0.0268*	0.0213	0.0201	0.0227	0.0227
	(0.0759)	(0.4357)	(0.1764)	(0.1390)	(0.1390)
ln(**No. filings**$_{(j,a)}$)	-0.0025	-0.0039	-0.0037**	-0.0029**	-0.0029**
	(0.1061)	(0.4003)	(0.0201)	(0.0487)	(0.0487)
Active ownership$_{(j,a)}$	0.0549	0.0641	0.0512***	0.0491***	0.0491***
	(0.1890)	(0.1014)	(0.0000)	(0.0000)	(0.0000)
Passive ownership$_{(j,a)}$	-0.0007	0.0011	-0.0073	0.0011	0.0011
	(0.9689)	(0.8972)	(0.4393)	(0.9044)	(0.9044)
ln(**Investor size**$_{(i,q)}$)	-0.0600***	-0.0609***	-0.0048	-0.0048	-0.0048
	(0.0059)	(0.0027)	(0.8487)	(0.8501)	(0.8501)
ln(**No. investor holdings**$_{(i,q)}$)	-0.2176***	-0.2233***	-0.0004	-0.0004	-0.0004
	(0.0000)	(0.0000)	(0.9918)	(0.9931)	(0.9931)
ln(**Investor size**$_{(i,q)}$) $\times$ ln(**No. investor holdings**$_{(i,q)}$)	0.0080***	0.0082***	-0.0001	-0.0001	-0.0001
	(0.0043)	(0.0016)	(0.9760)	(0.9752)	(0.9752)
Investor ownership$_{(i,j,q)}$	0.0260***	0.0265***	0.0235***	0.0235***	0.0235***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔInvestor ownership$_{(i,j,q,q-1)}$	0.0050	0.0052**	0.0051	0.0050	0.0050
	(0.2577)	(0.0319)	(0.2251)	(0.2353)	(0.2353)
d(**Bankrupt**$_{(j)}$)		0.0153***	0.0128**	0.0129**	0.0129**
		(0.0057)	(0.0349)	(0.0343)	(0.0343)
Observations	273,063	273,063	273,063	273,063	273,063
R^2	0.0192	0.0254	0.0048	0.0055	0.0043
R^2 **(Within)**	0.0184	0.0254	0.0050	0.0058	0.0056
F-statistic	265.84	339.18	62.769	54.281	34.253
p**-value (F-stat)**	0.0000	0.0000	0.0000	0.0000	0.0000
Year FE	yes	yes	yes	yes	yes
Company FE	yes	no	no	no	no
Industry FE	no	yes	no	yes	no
Investor FE	no	no	yes	yes	yes
Year $\times$ Industry FE	no	no	no	no	yes

The empirical evidence we presented in Section 3.5.3 indicates that the attention investors pay to companies that eventually go bankrupt ahead of bankruptcy is not driven by buy-and-hold stock return or by stock-return volatility, in line with the findings of Verrecchia (1982). We suggested that decreases in buy-and-hold stock return and increases in stock-return volatility observed before a company declares bankruptcy could indicate that professional investors have been selling their stock in that company. To examine the relationship between the amount of attention that professional investors pay to companies that later on become bankrupt and any changes in the holdings the investors have in these companies, we used detailed data on the investor–company level.

Figure 3.8 illustrates to what extent the professional investors we identified, such as investment banks, hedge funds, and asset management companies modified their holdings in any of the 269 companies that became bankrupt and any of the 853 companies in the five matched samples that remained solvent at any point between 24 months before and six months after a company declared bankruptcy. The figure shows that while these investors made hardly any changes in their holdings in the 853 companies that remained solvent, they started selling their shares in the companies that at the time were effectively bankrupt about one year before bankruptcy was actually declared.

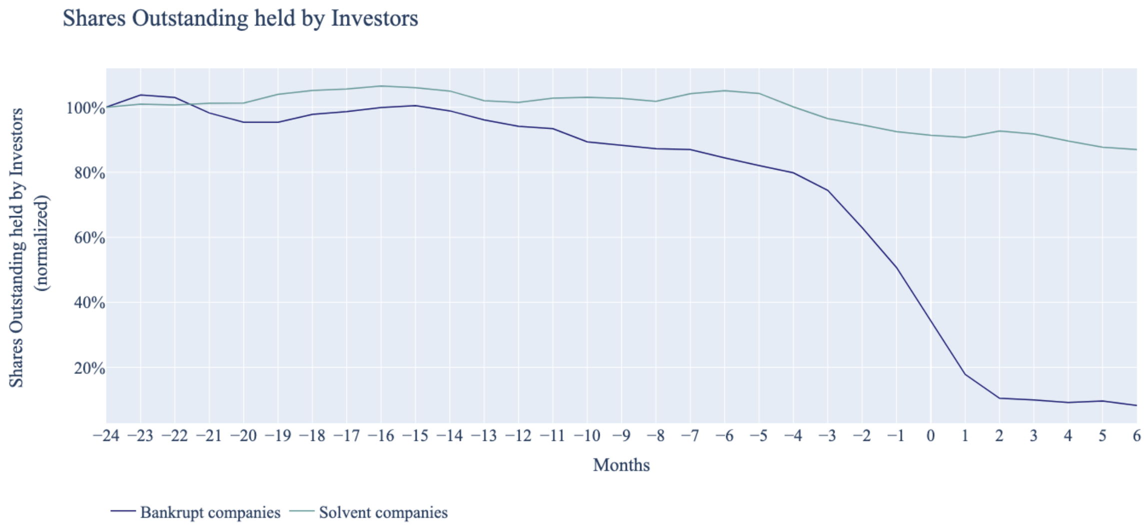


Figure 3.8: This figure illustrates the normalized level of holdings of identified professional investors such as investment banks, hedge funds, and asset management companies in total shares outstanding from 269 bankrupt and 999 matched companies. The figure spans the period 24 months before and six months after bankruptcy.

This is a remarkable observation, considering that, one year before each of the 269 companies became bankrupt, it exhibited very similar characteristics to those of its peer from the sample of 853 peer companies that remained solvent, including the apparent probability of bankruptcy. What both the finding that investors pay more attention to companies that later on go bankrupt before bankruptcy occurs and Figure 3.8 suggest is that the majority of professional investors we identified were able to distinguish confidently between the companies that would ultimately become bankrupt and those that would manage to overcome their financial difficulties and remain solvent. On the contrary, we expect that investors that either lack sufficiently detailed information on a company's prospects of solvency or the ability to interpret such information will either retain their holdings in a company that will go bankrupt later on or will reduce their holdings in all financially distressed companies, including those that eventually remain solvent.

It is conceivable that the results that Figure 3.8 illustrates might be driven by a hidden bias in the selection of the data we included in our samples or in the matching procedure. To check for unintentional bias, we repeated the analysis using data drawn from the entire CRSP mutual fund universe. The patterns this analysis produced (unreported) are very similar to the original ones, which indicates that there is no such bias.

To analyze the relationship between the share of attention that an individual investor pays to a specific company within a specific quarter during the period of interest and any subsequent changes in that investor's holdings in the company, we conducted a second regression analysis. In Equation 15, we define $\Delta Investor\ ownership_{(i,j,q+1,q)}$ as the quarterly change in the percentage share of stocks that investor i holds in company $j \in B \cup S$. In this regression, we used all the independent variables that reflect company and stock characteristics that are listed in Table 3.13 but added $Share\ of\ attention_{(i,j,q)}$ and the interaction $Share\ of\ attention_{(i,j,q)} \times d(Bankrupt_{(j)})$ as further independent variables. The results of this regression, which are displayed in Table 3.14, partly explain the changes in an investor's holdings in a particular company from quarter q to the next quarter $q+1$. As we control for company size, active and passive ownership, and the number of holdings an investor has $\Delta Investor\ ownership_{(i,j,q+1,q)}$:

$$\Delta Investor\ ownership_{(i,j,q+1,q)} = Investor\ ownership_{(i,j,q+1)} - Investor\ ownership_{(i,j,q)} \quad (15)$$

Again, as bankruptcy is a fixed company effect in our setting, we did not include this variable when we controlled for fixed company effects, which is why it is not listed in Column 1. However, we did include the interaction $Share\ of\ attention_{(i,j,q)} \times d(Bankrupt_{(j)})$ in Column 1, as it is not a company fixed effect. The regression results displayed in columns 1–5 of Table 3.13 are comparable with regard to several independent variables.

Table 3.14: This table reports the results from OLS regressions where the dependent variable is $\Delta investor\ ownership_{(i,j,q+1,q)}$. Independent variables include company and investor characteristics. All independent variables are defined in Appendix 3.D. Observations within the period of [-1, $+\infty$] quarters before and after bankruptcy are excluded from the regression analysis. All specifications include year fixed effects. We also include company fixed effects in column (1), industry fixed effects based on SIC 1 industry classification in column (2), investor fixed effects in column (3), industry and investor fixed effects in column (4) and investor and year $\times$ industry fixed effects in column (5). Across all columns, standard errors are clustered by company. p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	Pre-bankruptcy window				
	(1)	(2)	(3)	(4)	(5)
Dependent variable	ΔInvestor ownership$_{(i,j,q+1,q)}$				
Intercept	0.4704***	0.1453*	-0.1045	-0.0983	-0.0364
	(0.0000)	(0.0686)	(0.8282)	(0.8386)	(0.9404)
ln(**Firm size**$_{(j,a)}$)	-0.0160***	-0.0013	-0.0010	-0.0010	-0.0010
	(0.0003)	(0.1806)	(0.1818)	(0.1850)	(0.1850)
Leverage$_{(j,a)}$	-0.0011	-0.0020	-0.0024	-0.0019	-0.0019
	(0.5967)	(0.3064)	(0.1705)	(0.2815)	(0.2815)
ROA$_{(j,a)}$	0.0396***	0.0247***	0.0260***	0.0246***	0.0246***
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ln(**Analysts**$_{(j,a)}$)	0.0102***	0.0016	0.0020	0.0020	0.0020
	(0.0019)	(0.2185)	(0.1420)	(0.1496)	(0.1496)
ln(**Firm age**$_{(j,a)}$)	-0.1013***	-0.0150***	-0.0156***	-0.0155***	-0.0155***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CapEx$_{(j,a)}$	-0.0294	-0.0101	-0.0024	-0.0110	-0.0110
	(0.2150)	(0.3007)	(0.7830)	(0.2510)	(0.2510)
R&D$_{(j,a)}$	0.0306	0.0019	0.0048	0.0041	0.0041
	(0.2275)	(0.8997)	(0.4202)	(0.4975)	(0.4975)
Intangibles$_{(j,a)}$	-0.0034	-0.0153	-0.0182***	-0.0153***	-0.0153***
	(0.8665)	(0.1147)	(0.0002)	(0.0008)	(0.0008)
Tobin's Q$_{(j,a)}$	0.0008	0.0013**	0.0013***	0.0013***	0.0013***
	(0.2575)	(0.0360)	(0.0026)	(0.0037)	(0.0037)
Amihud$_{(j,a)}$	0.4876***	0.1554*	0.1092	0.1254	0.1254
	(0.0008)	(0.0845)	(0.2603)	(0.1915)	(0.1915)
B&h stock return$_{(j,a)}$	0.0080***	0.0123***	0.0126***	0.0125***	0.0125***
	(0.0001)	(0.0000)	(0.0008)	(0.0008)	(0.0008)
Stock return vola.$_{(j,a)}$	-0.0302***	-0.0327***	-0.0313***	-0.0322***	-0.0322***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ln(**No. filings**$_{(j,a)}$)	-0.0012	-0.0004	-0.0003	-0.0004	-0.0004
	(0.2835)	(0.4432)	(0.4483)	(0.3790)	(0.3790)
Active ownership$_{(j,a)}$	-0.0192	-0.0117**	-0.0110***	-0.0119***	-0.0119***
	(0.1428)	(0.0209)	(0.0001)	(0.0000)	(0.0000)
Passive ownership$_{(j,a)}$	-0.0198**	-0.0200***	-0.0210***	-0.0203***	-0.0203***
	(0.0359)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ln(**Investor size**$_{(i,q)}$)	-0.0040	-0.0020	0.0221	0.0221	0.0221
	(0.2405)	(0.7364)	(0.5007)	(0.5012)	(0.5012)
ln(**No. investor holdings**$_{(i,q)}$)	-0.0261***	-0.0230**	0.0012	0.0012	0.0012
	(0.0000)	(0.0209)	(0.9859)	(0.9860)	(0.9860)
ln(**Investor size**$_{(i,q)}$) $\times$ ln(**No. investor holdings**$_{(i,q)}$)	0.0014***	0.0011	-0.0016	-0.0016	-0.0016
	(0.0014)	(0.1374)	(0.7180)	(0.7186)	(0.7186)
Share of attention$_{(i,j,q)}$	0.0198*	0.0225**	0.0239**	0.0237**	0.0237**
	(0.0660)	(0.0192)	(0.0407)	(0.0453)	(0.0453)
Share of attention$_{(i,j,q)}$ $\times$ d(**Bankrupt**$_{(j)}$)	-0.0517**	-0.0546***	-0.0586***	-0.0588***	-0.0588***
	(0.0227)	(0.0030)	(0.0071)	(0.0073)	(0.0073)
d(**Bankrupt**$_{(j)}$)		-0.0023	-0.0018	-0.0020	-0.0020
		(0.3692)	(0.2073)	(0.1762)	(0.1762)
Observations	280,071	280,071	280,071	280,071	280,071
R^2	0.0030	0.0024	0.0028	0.0028	0.0043
R^2 **(Within)**	0.0049	0.0032	0.0035	0.0035	0.0043
F-statistic	42.225	32.503	37.141	28.290	35.622
p-**value (F-stat)**	0.0000	0.0000	0.0000	0.0000	0.0000
Year FE	yes	yes	yes	yes	yes
Company FE	yes	no	no	no	no
Industry FE	no	yes	no	yes	no
Investor FE	no	no	yes	yes	yes
Year $\times$ Industry FE	no	no	no	no	yes

The coefficient of the independent variables ROA and buy-and-hold stock return is statistically significant and positive. Furthermore, the relationships between the independent variables company age, stock return volatility, and passive ownership and the quarterly change in investor ownership are statistically significant and negative. In particular, the relationships between the independent variables buy-and-hold stock return and stock return volatility and the dependent variable $\Delta Investor\ ownership_{(i,j,q+1,q)}$ are largely intuitive, indicating that past stock performance explains future changes in stock holdings.

The coefficient of the interaction $Share\ of\ attention_{(i,j,q)} \times d(Bankrupt_{(j)}$ is negative and statistically significant at the 5% level (p-values < 0.05) when we control for year and company fixed effects and statistically significant at the 1% level (p-values < 0.01) in all other specifications. In contrast to Drake et al. (2020) and to the positive relationship between the attention that investors pay at a given point in time to a particular company and prospective changes in their holdings in that company, the empirical results displayed in Table 3.14 show that a high degree of attention paid to financially distressed companies by investors indicates that these companies will go bankrupt in the relatively near future. Furthermore, our empirical results indicate that professional investors who focus on companies that will declare bankruptcy in the near future start selling their holdings in these companies at an early stage. Therefore, a high degree of investor attention paid to financially distressed companies does help predict decreases in stock returns and bankruptcy in the relatively near future.

3.6 Conclusion

For the purposes of our study, we relied on data from the EDGAR log-files, which record requests users make for company information held on the EDGAR server. Our analysis of the partly anonymized IP addresses of 2,481 market actors who requested filings stored in the EDGAR database enabled us to differentiate between specific groups of professional investors and other types of users who accessed the database. This analysis also enabled us to identify specific professional investors and to combine the relevant data with data on the holdings these investors had in the companies in our sample. The latter data were derived from Form 13F filings. Using these data, we investigated empirically patterns in the attention that investors pay to financially distressed companies that eventually go bankrupt, as well as changes in the stock these investors hold in such companies.

Users who seek information on specific US-listed companies typically access their SEC filings on the EDGAR server. Thereby, the number of requests depends on company characteristics, such as size, performance, and market capitalization. Furthermore, internet traffic on the EDGAR server is not stable but fluctuates considerably. All these factors posed a real challenge in terms of how to best handle the EDGAR log-file dataset.

To deal with the potential confounding effects of particular factors on the number of requests submitted at a particular point in time to the EDGAR server, we used propensity score matching. This approach enabled us to discern patterns in the searches that investors conducted to gather information on financially distressed companies before these became officially bankrupt. It also allowed us to control for time-related factors and for factors related to company characteristics that might influence such patterns. To confirm our initial results, we applied five common bankruptcy prediction models (Altman, 1968; Ohlson, 1980; Campbell et al., 2008; Merton, 1974) to five subsamples of 269 companies that remained solvent and that we matched to the sample of bankrupt companies on the basis of the independent variables we derived from these models. We furthermore conducted further tests using placebo subsamples and additional robustness checks, all of which confirmed that our empirical results are robust.

Our results are in line with economic theory. Therefore, our study extends empirical research on the attention investors pay to certain categories of companies. Previous research suggests that a perfectly efficient capital market where all stock prices fully reflect all available information is not likely to be possible (Grossman and Stiglitz, 1980). Market prices reflect the aggregated amount of information that all investors who are active during a given period collect and process. This information, however, becomes available gradually and is often incomplete (Verrecchia, 1982). For that reason, stock prices reveal at best a delayed response to the process of gathering and processing information. Therefore, skilled investors have an incentive to gain an information advantage up to the point where the marginal cost of information gathering exceeds the corresponding marginal return (Kacperczyk et al., 2016; Lee and So, 2015). Potential bankruptcy in particular offers investors the incentive to react to changes in a company's financial status (Lo, 2004, 2019; Kim et al., 2011). Our empirical analysis shows that market actors, particularly professional investors, conduct significantly more research on companies that are effectively, though not yet officially, bankrupt than on companies that, although financially distressed, remain solvent in the foreseeable future. Furthermore, we provide empirical evidence that investors manage their portfolio on the basis of the information they have gathered and processed on specific companies therein.

Our analysis of the attention investors pay to effectively bankrupt companies extends the findings of Drake et al. (2020) and of the relevant literature more generally and shows that the amount and type of information that professional investors collect on such companies is associated with a reduction in their holdings in these companies before bankruptcy occurs. The higher demand for information on companies that are effectively bankrupt indicates that market actors can anticipate a prospective bankruptcy at least two years before it occurs. Furthermore, we find that professional investors, such as investment banks, hedge funds or asset management companies, translate their information advantage into stock-selling at around 11–14 months before a company goes bankrupt. As stock prices typically start to decrease substantially 4–5 months before the bankruptcy event, we conclude that at least some (skilled) professional investors are able to utilize disclosed company information to increase the accuracy of their prediction as to when a company will go bankrupt.

The present study contributes to the literature in two major ways: First, it sheds light on the attention investors pay to financially distressed companies. Second, it reveals that it is possible to predict bankruptcy more accurately by utilizing particular types of data. We found that professional investors who acquired extensive information on companies that eventually went bankrupt also reduced their holdings about one year before these companies declared bankruptcy. This indicates that certain professional investors, such as investment banks, hedge funds, and asset management companies, start reducing their holdings in companies that will eventually go bankrupt at an early stage, but not in companies that, although financially distressed, remain solvent. In sum, our analysis shows that it is possible to improve the accuracy of prediction models by introducing an explanatory variable that is based on either the amount of attention investors pay to a company or on the observable holdings professional investors have in a company.

Our findings also suggest that the information disclosed in Form 10-K and Form 10-Q filings, which account for about 21% of all requests submitted to the EDGAR server, can help investors assess a company's financial health and prospects. Although our analysis does not focus on these filings, there is no question that accounting information plays an important role in evaluating a company's financial health. Form 10-K and Form 10-Q filings are publicly available. However, it appears that only specific market actors are able to identify companies that are effectively bankrupt ahead of actual bankruptcy. This leads us to conclude that accounting expertise is highly valuable in the case of bankruptcy prediction. Since the global financial crises of 2007 and 2008, the number of corporate bankruptcies has been unusually low globally. However, the impact of the COVID-19 pandemic on the economy is likely to increase this number substantially in the next two years. Now more than ever, having a solid understanding of accounting and a strong relevant education are crucial to making the right investment decisions.

Appendix 3.A EDGAR Log-Files Dataset

Table 3.15: This table shows how requests submitted to the EDGAR server developed over time. Our records start in February 2003 and end in June 2017, representing the entire available EDGAR log-file dataset. The table shows that the total number of requests made per year increased exponentially during that period, both overall and in the subsamples of requests we examined. Specifically, about 60% of the entire number of requests were made between January 2015 and June 2017. Of these requests, 6.82% were submitted by identified market actors and 11.27% from within 30 identified financial centers.

	Total requests		Requests from identified market actors		Requests form within one of 30 financial centers	
Feb. 2003–June 2017	13,708,881,830	100%	935,160,095	100%	1,544,483,094	100%
2003	28,593,371	0.21%	2,012,430	0.22%	2,761,646	0.18%
2004	82,686,138	0.60%	4,925,064	0.53%	4,543,615	0.29%
2005	49,375,491	0.36%	3,335,830	0.36%	6,063,395	0.39%
2006	72,568,870	0.53%	15,945,935	1.71%	7,760,074	0.50%
2007	125,874,642	0.92%	31,452,419	3.36%	11,042,013	0.71%
2008	143,397,670	1.05%	13,791,317	1.47%	19,277,552	1.25%
2009	326,615,337	2.38%	26,497,778	2.83%	41,654,113	2.70%
2010	523,958,193	3.82%	63,551,643	6.80%	86,491,917	5.60%
2011	548,472,977	4.00%	40,943,430	4.38%	69,213,321	4.48%
2012	826,035,384	6.03%	65,053,138	6.96%	113,594,424	7.35%
2013	1,422,710,478	10.38%	141,511,794	15.13%	120,952,088	7.83%
2014	1,592,288,454	11.62%	120,674,003	12.90%	166,061,966	10.75%
2015	2,093,641,552	15.27%	175,911,486	18.81%	252,308,648	16.34%
2016	3,405,079,232	24.84%	99,411,848	10.63%	354,589,556	22.96%
2017	2,467,584,041	18.00%	130,141,980	13.92%	288,168,766	18.66%

Table 3.16: This table shows the number of requests made by bots and spiders to the EDGAR server. These requests were made by various data-crawling companies and with various search engines. The requests made from the respective IP addresses account for 27.11% of all requests made to the EDGAR server within the period February 2003 to June 2017. The high number of requests made from these IP addresses shows how important it is to clean the data by excluding automated requests.

Bots and spiders	No. of identified IP address blocks	Total requests	Share in total requests	Share in requests made by identified bots
Diffbot	143.608	2,257,145,741	16.46%	60.72%
Alphabet	3.906	594,127,759	4.33%	15.98%
Microsoft	13.934	314,656,288	2.30%	8.47%
Yahoo	2.606	252,624,635	1.84%	6.80%
Baidu	1.126	166,890,225	1.22%	4.49%
Yandex	905	112,665,174	0.82%	3.03%
Ahrefsbot	8	10,733,049	0.08%	0.29%
Youdao	1	4,151,666	0.03%	0.11%
Twitter	3	2,542,348	0.02%	0.07%
Blekko	12	883.332	0.01%	0.02%
Facebook	1,230	448.975	0.00%	0.01%
Easou	1	229.306	0.00%	0.01%
Sogou	2	3.368	0.00%	0.00%
Gorgor	1	2.364	0.00%	0.00%
Lycos	18	1.057	0.00%	0.00%
Duckduckgo	1	161	0.00%	0.00%
Exalead	3	86	0.00%	0.00%
Gigablast	1	7	0.00%	0.00%
Total	167.366	3,717,105,541	27.11%	100%

Table 3.17: This table reports the distribution of total requests submitted to the EDGAR server for the top 20 types of forms. The dataset used in this study covers all types of forms in the EDGAR database. It is worth mentioning that almost 92% of all requests made to EDGAR concerned these 20 types of forms. Form filings 4, 8-K, 10-Q, and 10-K are among the most requested types and account for 77.47% of all requests.

Categories of filings	Total requests	Share in total requests	Share in requests from identified hedge funds	Share in requests from identified investment banks	Share in requests from identified asset management companies
4	5,507,792,098	40.18%	64.87%	53.76%	52.57%
8-K	2,215,277,918	16.16%	10.33%	11.32%	11.10%
10-Q	1,595,752,741	11.64%	5.60%	10.45%	8.22%
10-K	1,301,635,860	9.49%	3.10%	10.00%	6.61%
DEF 14A	333,033,500	2.43%	0.56%	0.77%	10.36%
SC 13G/A	273,388,237	1.99%	1.36%	0.36%	1.58%
3	180,940,151	1.32%	2.23%	2.50%	0.30%
SC 13G	149,854,860	1.09%	0.65%	0.23%	0.85%
4/A	135,302,869	0.99%	1.68%	0.33%	0.87%
SC 13D/A	128,455,193	0.94%	0.47%	0.29%	0.51%
424B2	111,380,130	0.81%	0.86%	0.91%	0.29%
10-K/A	87,318,656	0.64%	0.31%	0.37%	0.26%
DEFA14A	79,197,560	0.58%	0.35%	0.44%	0.44%
424B3	75,718,772	0.55%	0.36%	0.61%	0.27%
UPLOAD	73,616,638	0.54%	0.23%	0.06%	0.29%
CORRESP	69,298,248	0.51%	0.18%	0.07%	0.15%
S-1/A	68,571,277	0.50%	0.19%	0.77%	0.37%
S-4	65,369,706	0.48%	0.07%	0.15%	0.06%
SC 13D	63,360,158	0.46%	0.16%	0.14%	0.26%
425	57,344,816	0.42%	0.31%	0.46%	0.29%
Total	12,572,609,388	91.71%	93.90%	94.00%	95.64%

Table 3.18: This table reports all requests submitted to the EDGAR server from any IP address within one of the 30 listed financial centers. Requests made from IP addresses within one of 30 identified financial centers account for 11.27% of all requests made to the EDGAR server. As we restricted our analysis to US-listed companies, six US financial centers are among the top ten financial centers on the basis of the number of requests submitted.

Financial Center	Total requests	Share in total requests	Share in requests made from identified financial centers	No. of identified hedge funds	No. of identified investment banks	No. of identified asset management companies
New York	448,927,396	3.27%	29.07%	49	10	18
Shanghai	138,826,974	1.01%	8.99%	0	0	0
Chicago	106,531,491	0.78%	6.90%	5	0	11
Beijing	103,782,066	0.76%	6.72%	0	1	0
San Francisco	97,560,355	0.71%	6.32%	2	1	5
Boston	94,909,998	0.69%	6.15%	5	0	7
Los Angeles	93,003,053	0.68%	6.02%	2	3	4
Washington	89,175,984	0.65%	5.77%	2	0	2
Paris	76,108,367	0.56%	4.93%	0	0	0
Toronto	67,993,699	0.50%	4.40%	0	0	0
London	64,707,686	0.47%	4.19%	8	9	5
Hong Kong	40,837,134	0.30%	2.64%	0	2	0
Shenzhen	39,429,327	0.29%	2.55%	0	1	0
Sydney	19,897,762	0.15%	1.29%	0	1	1
Singapore	13,248,362	0.10%	0.86%	0	1	1
Frankfurt	9,106,882	0.07%	0.59%	0	0	0
Taipei	8,758,404	0.06%	0.57%	0	0	0
Tokyo	8,167,286	0.06%	0.53%	0	0	0
Seoul	7,761,687	0.06%	0.50%	0	1	1
Montreal	5,521,096	0.04%	0.36%	0	0	0
Vancouver	4,796,849	0.03%	0.31%	0	0	1
Zurich	1,743,158	0.01%	0.11%	0	0	0
Munich	979.809	0.01%	0.06%	0	0	0
Melbourne	847.426	0.01%	0.05%	0	0	0
Luxembourg	569.873	0.00%	0.04%	0	0	0
Dubai	467.530	0.00%	0.03%	0	0	0
Osaka	396.508	0.00%	0.03%	0	0	0
Abu Dhabi	311.956	0.00%	0.02%	0	0	0
Geneva	84.195	0.00%	0.01%	0	0	0
Casablanca	30.781	0.00%	0.00%	0	0	0
Total	1,544,483,094	11.27%	100%	73	30	56

Appendix 3.B Sample Construction

Table 3.19: This table reports the mean values of the metric accounting-based and market-based independent variables for the samples of bankrupt companies and their solvent matches, the p-values of the t-test, and the mean caliper distances. The p-values indicate that there are no highly statistically significant differences for almost any metric variable. The subsequent review of the caliper bandwidth showed that the mean caliper distance of the 269 matched pairs in all five samples tends to be far below the caliper distance that Rosenbaum and Rubin (1983) recommend.

Altman (1968)	Mean bankrupt companies (N = 269)	Mean matched companies (N = 269)	p-value (t-test)	Mean caliper distance
WC_TA	0.13	0.15	0.12	0.13
RE_TA	–1.47	–1.38	0.59	0.05
$EBIT\_TA$	–0.16	–0.13	0.20	0.11
MVE_TL	1.46	1.62	0.59	0.05
S_TA	1.05	0.99	0.32	0.09
Ohlson (1980)	Mean bankrupt companies (N = 269)	Mean matched companies (N = 269)	p-value (t-test)	Mean caliper bandwidth
TL_TA	0.77	0.73	0.12	0.14
$OENEG$	0.30	0.20		
WC_TA	0.13	0.14	0.45	0.07
CL_CA	0.76	0.71	0.10	0.10
NI_TA	–0.27	–0.23	0.06	0.16
NI_TWO	0.74	0.60		
FU_TL	–0.35	–0.31	0.41	0.07
CH_NI	–0.19	–0.17	0.47	0.06
$RSIZE$	–18.87	–18.79	0.51	0.06
Campbell et al. (2008) A	Mean bankrupt companies (N = 269)	Mean matched companies (N = 269)	p-value (t-test)	Mean caliper bandwidth
NI_TAA	–0.25	–0.22	0.10	0.14
TL_TAA	0.73	0.70	0.05	0.17
EXC_RET	–0.07	–0.05	0.18	0.12
$SIGMA$	0.85	0.81	0.18	0.12
$RSIZE$	–18.87	–18.91	0.76	0.03
Campbell et al. (2008) B	Mean bankrupt companies (N = 269)	Mean matched companies (N = 269)	p-value (t-test)	Mean caliper bandwidth
NI_MVTA	–0.17	–0.15	0.07	0.16
TL_MVTA	0.63	0.58	0.01	0.23
CA_MVTA	0.10	0.10	0.12	0.14
MB	1.55	1.51	0.84	0.02
EXC_RET	–0.07	–0.05	0.11	0.14
$SIGMA$	0.85	0.81	0.07	0.16
$RSIZE$	–18.87	–18.91	0.80	0.02
$PRICE$	0.72	0.88	0.03	0.19
Merton (1974)	Mean bankrupt companies (N = 269)	Mean matched companies (N = 269)	p-value (t-test)	Mean caliper bandwidth
MVA ($US\$K$)	333,694	328,129	0.96	0.00
$SIGMA\_MVA$	1.24	1.22	0.58	0.05
MVE ($US\$K$)	331,234	325,914	0.97	0.00
$SIGMA\_MVE$	0.84	0.84	0.83	0.02

Table 3.20: This table shows the mean values of the metric accounting-based and market-based independent variables for the matched companies and the placebo companies, the p-values of the t-test, and the mean caliper distances. The p-values indicate that there are no highly statistically significant differences for almost any metric variable. The subsequent review of the caliper bandwidth showed that, in most cases, the mean caliper distance of the 269 matched pairs in all five samples is far below the caliper distance that Rosenbaum and Rubin (1983) recommend.

Altman (1968)	Mean matched companies (N = 269)	Mean placebo companies (N = 269)	p-value (t-test)	Mean caliper distance
WC_TA	0.15	0.17	0.30	0.09
RE_TA	–1.38	–1.25	0.45	0.07
$EBIT\_TA$	–0.13	**–0.11**	0.21	0.11
MVE_TL	1.62	1.71	0.76	0.03
S_TA	0.99	0.97	0.83	0.02
Ohlson (1980)	Mean matched companies (N = 269)	Mean placebo companies (N = 269)	p-value (t-test)	Mean caliper distance
TL_TA	0.73	0.69	0.02	0.20
$OENEG$	0.20	0.11		
WC_TA	0.14	0.17	0.10	0.14
CL_CA	0.71	0.67	0.17	0.12
NI_TA	–0.23	–0.19	0.09	0.15
NI_TWO	0.60	0.49		
FU_TL	–0.31	–0.26	0.43	0.07
CH_NI	–0.17	–0.16	0.89	0.01
$RSIZE$	–18.79	–18.67	0.35	0.08
Campbell et al. (2008) A	Mean matched companies (N = 269)	Mean placebo companies (N = 269)	p-value (t-test)	Mean caliper distance
NI_TAA	–0.22	–0.19	0.20	0.11
TL_TAA	0.70	0.66	0.08	0.15
EXC_RET	–0.05	–0.04	0.09	0.15
$SIGMA$	0.81	0.77	0.06	0.16
$RSIZE$	–18.91	–18.87	0.76	0.03
Campbell et al. (2008) B	Mean matched companies (N = 269)	Mean placebo companies (N = 269)	p-value (t-test)	Mean caliper distance
NI_MVTA	–0.15	–0.13	0.14	0.13
TL_MVTA	0.58	0.55	0.33	0.09
CA_MVTA	0.10	0.11	0.28	0.09
MB	1.51	1.48	0.87	0.01
EXC_RET	–0.05	–0.05	0.81	0.02
$SIGMA$	0.81	0.74	0.01	0.22
$RSIZE$	–18.91	–18.79	0.42	0.07
$PRICE$	0.88	1.03	0.05	0.17
Merton (1974)	Mean matched companies (N = 269)	Mean placebo companies (N = 269)	p-value (t-test)	Mean caliper bandwidth
MVA ($US\$K$)	328,129	343,420	0.90	0.01
$SIGMA\_MVA$	1.22	1.19	0.45	0.07
MVE ($US\$K$)	325,914	341,536	0.89	0.01
$SIGMA\_MVE$	0.84	0.82	0.69	0.04

Appendix 3.C Bankruptcy Prediction Models

Table 3.21: This table shows the mean and median values for each independent variable used in the bankruptcy prediction models.

	Solvent companies				Bankrupt companies			
Period	Jan. 1st 1983 – March 31st, 2004		April 1st, 2004 – Sept. 30th, 2015		Jan. 1st 1983 – March 31st, 2004		April 1st, 2004 – Sept. 30th, 2015	
Observations	68,519		36,056		611		269	
Altman (1968)	Mean	Median	Mean	Median	Mean	Median	Mean	Median
WC_TA	0.29	0.27	0.28	0.24	0.10	0.05	0.13	0.08
RE_TA	–0.20	0.10	–0.49	0.06	–0.74	–0.25	–1.47	–0.67
$EBIT\_TA$	0.01	0.07	0.01	0.06	–0.12	–0.05	–0.16	–0.06
MVE_TL	5.54	2.10	5.27	2.52	1.74	0.29	1.46	0.31
S_TA	1.13	1.05	1.00	0.86	1.08	0.97	1.05	0.86
Ohlson (1980)	Mean	Median	Mean	Median	Mean	Median	Mean	Median
TL_TA	0.48	0.48	0.48	0.47	0.72	0.78	0.77	0.83
$OENEG$	0.03	0.00	0.04	0.00	0.21	0.00	0.30	0.00
WC_TA	0.29	0.27	0.28	0.24	0.10	0.05	0.13	0.08
CL_CA	0.50	0.42	0.46	0.40	0.84	0.83	0.76	0.73
NI_TA	–0.04	0.03	–0.03	0.03	–0.22	–0.13	–0.27	–0.20
NI_TWO	0.21	0.00	0.23	0.00	0.58	1.00	0.74	1.00
FU_TL	0.02	0.15	0.01	0.14	–0.29	–0.08	–0.35	–0.10
CH_NI	0.00	0.02	0.03	0.03	–0.29	–0.33	–0.19	–0.18
$RSIZE$	–17.44	–17.55	–17.12	–17.12	–18.74	–18.92	–18.87	–19.10
Campbell et al. (2008) A	Mean	Median	Mean	Median	Mean	Median	Mean	Median
NI_TAA	–0.03	0.03	–0.03	0.03	–0.20	–0.13	–0.25	–0.20
TL_TAA	0.45	0.45	0.45	0.44	0.70	0.78	0.73	0.82
EXC_RET	–0.01	–0.01	–0.00	–0.00	–0.06	–0.08	–0.07	–0.09
$SIGMA$	0.60	0.51	0.48	0.41	1.05	1.18	0.85	0.85
$RSIZE$	–17.44	–17.55	–17.12	–17.12	–18.74	–18.92	–18.87	–19.10
Campbell et al. (2008) B	Mean	Median	Mean	Median	Mean	Median	Mean	Median
NI_MVTA	–0.02	0.02	–0.02	0.02	–1.40	-0.12	–0.17	–0.15
TL_MVTA	0.36	0.32	0.32	0.29	0.64	0.77	0.63	0.77
CA_MVTA	0.09	0.05	0.11	0.08	0.07	0.03	0.10	0.06
MB	2.56	1.71	2.77	1.96	1.60	0.62	1.55	0.60
EXC_RET	–0.01	–0.01	–0.00	–0.00	–0.06	–0.08	–0.07	–0.09
$SIGMA$	0.60	0.51	0.48	0.41	1.05	1.18	0.85	0.85
$RSIZE$	–17.44	–17.55	–17.12	–17.12	–18.74	–18.92	–18.87	–19.10
$PRICE$	1.95	2.38	2.11	2.70	0.80	0.66	0.72	0.49
Merton (1974)	Mean	Median	Mean	Median	Mean	Median	Mean	Median
$MVA\ (US\$M)$	823	110	1.768	456	222	32	334	57
$SIGMA\_MVA$	0.73	0.64	0.62	0.51	1.35	1.62	1.24	1.51
$MVE\ (US\$M)$	821	106	1.767	456	220	31	331	55
$SIGMA\_MVE$	0.64	0.57	0.51	0.45	1.02	1.08	0.84	0.81

We estimated the bankruptcy prediction models of Altman (1968), Ohlson (1980), Campbell et al. (2008), and Merton (1974) using data covering the periods January 1st, 1983 to June 30th, 2005 and April 1st, 2004 to December 31st, 2016 to verify the validity of our propensity score matching. These models are variants of a general linear model (GLM) with a logistic distribution function (Nelder and Wedderburn, 1972). The dependent variable is company bankruptcy. A company was classified as "bankrupt" (y_i=1) if it had filed for bankruptcy under Chapter 7 or Chapter 11 within 15 months after the most recent balance-sheet date on the annual financial statement that we consulted.

The main difference between the models we applied here, apart from the two different periods they cover, is that they use different independent variables to predict bankruptcy. These variables are either accounting-based or market-based and capture important company characteristics. Table 3.2 provides an overview of the independent variables that Altman (1968), Ohlson (1980), Campbell et al. (2008), and Merton (1974) used. We extracted our independent variables from the Compustat database and the CRSP database. We control for year and industry effects, according to the SIC 1 industry classification. We excluded all companies in the category "Money & Finance" of the Fama–French 12-industry classification scheme.

To ensure that our observations are reliable, it is necessary to confirm that there are no dependencies between individual observations. The most common method for this purpose is to use only each company's most recent available annual financial statement and the respective market data. However, there are two problems with this approach: First, this reduces the total number of firm–year observations to the number of companies in the sample. Second, there are differences between companies that remained solvent in the longer term and companies that eventually went bankrupt in the temporal distribution of the most recent observations available for each category. In the case of the companies that remained solvent, the majority of the most recent available observations relate to the last year of the period of interest. In the case of the companies that later on went bankrupt, these observations are spread over the entire period of interest.

We overcame both problems by using a simulation technique to estimate the bankruptcy prediction models. First, we selected the most recent available observations on the companies that were effectively, but not yet officially, bankrupt. Next, we selected randomly one observation per company in the "solvent" category. However, in the latter case, we limited the random selection to observations that match both the temporal distribution and the industry distribution of the effectively bankrupt companies. We repeated the second step to estimate 10,000 bankruptcy prediction models, following Altman (1968), Ohlson (1980), Campbell et al. (2008), and Merton (1974) for two different periods, i.e., January 1st, 1983 to June 30th, 2005 (Period I) and April 1st, 2004 to December 31st, 2016 (Period II). We then calculated the mean values of the coefficients and used these to verify the validity of the propensity score matching.

The calculated mean values of the coefficients display the expected values and signs. Table 3.22 shows the pseudo-R^2 and the AUC of the bankruptcy prediction models derived from 10,000 simulated samples. We applied the mean model coefficients on the in-sample period (model coefficients derived from period I applied on period I, and model coefficients derived from period II applied on period II) and on the out-of-sample period (model coefficients derived from period I applied on period II). The validity measures show that every estimated model can distinguish accurately between companies that remained solvent and companies that eventually went bankrupt in the case of all company observations within a certain period. The results of the estimated bankruptcy prediction models are completely in line with the results of Altman (1968), Ohlson (1980), Campbell et al. (2008), as well as Merton (1974) in conjunction with Bharath and Shumway (2004). Therefore, we can apply the bankruptcy prediction models to validate the composition of the final sample that we derive by means of propensity score matching.

Table 3.22: This table reports the validity measures we used in the five bankruptcy prediction models derived from Altman (1968), Ohlson (1980), Campbell et al. (2008), as well as Merton (1974) for the periods January 1st, 1983 – June 30th, 2005 (Period I) and April 1st, 2004 – December 31st, 2016 (Period II). To obtain the reported values, we applied a logistic distribution function and the mean estimated coefficient values we derived from analyzing 10,000 samples. The AUC values in particular indicate that the discriminatory power of all estimated bankruptcy prediction models is very high and in line with the literature.

Observation period of the dependent variable	Jan. 1st, 1983 – June 30th, 2005		July 1st, 2005 – Dec. 31st, 2016	
Observation period of the independent variables	Jan. 1st, 1983 – March 31st, 2004		April 1st, 2004 – Sept. 30th, 2015	
	Pseudo-R^2	AUC	Pseudo-R^2	AUC
Altman (1968) I	0.2444	0.80		0.79
Altman (1968) II			0.2819	0.87
Ohlson (1980) I	0.3116	0.83		0.88
Ohlson (1980) II			0.3844	0.90
Campbell et al. (2008) A I	0.3657	0.88		0.89
Campbell et al. (2008) A II			0.4037	0.91
Campbell et al. (2008) B I	0.4035	0.89		0.90
Campbell et al. (2008) B II			0.4485	0.92
Merton (1974) I		0.83		
Merton (1974) II				0.95

Appendix 3.D Variable Definitions

Table 3.23: This table presents and defines the variables we used. We constructed the variables that capture investor attention on the basis of the EDGAR log-file dataset. Furthermore, we derived the company variables from the CRSP and Compustat databases and from EDGAR filings, particularly from 13D(/A) and 13G(/A) filings. The investor variables were derived from Form 13F filings.

Variable	Definition
Attention variables	
Attention$_{(g,j,w)}$	The relative attention in week w (or month m or quarter q) on a company j from a certain group g.
Abn. attention$_{g,w}$	The degree of abnormal attention, measured as the difference between the attention paid to bankrupt companies and the attention paid to matched solvent companies in a sample, normalized by the attention paid to matched solvent companies in the same sample. This measure captures directly the percentage level of abnormal attention that bankrupt companies receive from a certain group g in week w (or month m or quarter q).
Share of attention$_{(i,j,q)}$	The share of attention, measured as the ratio of all requests an investor i makes for information on a single company j in quarter q, divided by the total requests for information that this specific investor i submitted to the EDGAR server in the same quarter.
Company variables	
ln(Company size$_{(j,a)}$)	The natural logarithm of company j's total assets in a given fiscal year a, winsorized at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles.
Leverage$_{(j,a)}$	Company j's total debt divided by its total assets for a given fiscal year a, winsorized at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles.
ROA$_{(j,a)}$	Company j's earnings before interest, tax, depreciation and amortization (EBITDA) divided by its total assets for a given fiscal year a, winsorized at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles.
ln(Analysts$_{(j,a)}$)	The natural logarithm of the number of analysts who cover company j in the fiscal year a.
ln(Company age$_{(j,a)}$)	The number of years since IPO of company j for a given fiscal year a.
CapEx$_{(j,a)}$	Company j's capital expenditures (CapEx) divided by its total assets for a given fiscal year a, winsorized at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles.
R&D$_{(j,a)}$	Company j's research and development expenditures (R&D) divided by its total assets for a given fiscal year a, winsorized at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles.
Intangibles$_{(j,a)}$	Company j's book value of intangible assets divided by its total assets for a given fiscal year a, winsorized at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles.

Company variables	
Tobin's Q$_{(j,a)}$	Company j's market value of equity plus its book value of total assets minus its book value of equity divided by its book value of total assets for a given fiscal year a, winsorized at the 5th and 95th percentiles
Amihud$_{(j,a)}$	The liquidity measure that is proposed by Amihud (2002) of company j's stock for a given fiscal year a, winsorized at the 5th and 95th percentiles.
B&h stock returns$_{(j,a)}$	Company j's buy & hold stock return for a given fiscal year a, winsorized at the 5th and 95th percentiles.
Stock return volatility$_{(j,a)}$	Company j's annualized stock return volatility for a given fiscal year a, winsorized at the 5th and 95th percentiles.
ln(No. filings$_{(j,a)}$)	The natural logarithm of the sum of filings which company j filed within a given fiscal year a, winsorized at the 5th and 95th percentiles.
ln(No. filings$_{(j,q)}$)	the natural logarithm of the sum of filings which company j filed within a given fiscal quarter q, winsorized at the 5th and 95th percentiles.
Active ownership$_{(j,a)}$	The total active ownership on company j as filed by form 13D(/A) filing at the end of the fiscal year a, winsorized at the 5th and 95th percentiles.
Passive ownership$_{(j,a)}$	The total passive ownership on company j as filed by form 13G(/A) filing at the end of the fiscal year a, winsorized at the 5th and 95th percentiles.
Complicated firm$_{(j,a)}$	The measure of company j's complexity, derived from Cohen and Lou (2012), in fiscal year a, winsorized at the 5th and 95th percentiles.
Investor variables	
ln(Investor size$_{(i,q)}$)	The natural logarithm of investor i's total assets under management corresponding to non-derivative long positions, as reported in the Form 13F filing at the end of fiscal quarter q, winsorized at the 5th and 95th percentiles.
ln(No. investor holdings$_{(i,q)}$)	The natural logarithm of investor i's number of non-derivative long positions, as reported in the Form 13F filing at the end of fiscal quarter q, winsorized at the 5th and 95th percentiles.
Investor ownership$_{(i,j,q)}$	The share of total shares outstanding that investor i holds in company j, as reported in the Form 13F filing at the end of fiscal quarter q, winsorized at the 5th and 95th percentiles.

Watch the votes: How unwanted directors hurt firm performance

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Abstract

Are shareholder votes informative of a director's abilities to efficiently monitor and advise management in order to maximize shareholder value? We find firms with "unwanted" directors, i.e. those with less votes for (re)election than their peers, experience an economically sizeable decline in firm value and operating performance. This effect is more pronounced when more unwanted directors are on a firm's board. An analysis of sudden director deaths as well as a trading strategy also support these results and address concerns of endogeneity. Overall, the evidence indicates shareholder votes to contain insights about the effectiveness of a firm's corporate governance.

Keywords: corporate governance, directors, firm value, voting

JEL classification: G3, G30, G34

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4.1 Introduction

In an organizational structure the directors' job is to monitor and advise the company's management in order to protect shareholders' interests. Poor director performance can have adverse effects for the company and thus for shareholders, e.g. if monitoring is weak, managers may engage in empire building to increase power and influence in the organization (Jensen, 1986), while in the absence of good advise managers are more likely to make value-destroying decisions (Renjie and Verwijmeren, 2019). As agency theory suggests, a well-functioning board of directors is, therefore, key to protect shareholders' interests (Masulis and Zhang, 2019). Given that shareholders express their satisfaction with the board of directors through voting at director elections (Chen and Guay, 2018), we aim to address the question whether shareholder votings additionally give important insights about the level of monitoring and advising exerted by directors and are thus informative of future firm value.

Some recent studies have addressed the informational content of director election outcomes, but it remained unclear whether they are insightful of a firm's future value. While Chen and Guay (2018) state that director voting is a proxy for shareholders' satisfaction with directors, Cai et al. (2009) are sceptical with respect to the effectiveness of voting. Aggarwal et al. (2019) find that voting is an effective mechanism to bring about changes in a firm's corporate governance and board structure and that directors receiving more dissent votes have less opportunities in the director labor market, while Fos et al. (2018) find director elections to be a fundamental feature of corporate governance since they induce directors to monitor management more rigorously.

Regarding the relationship between the effectiveness of corporate governance and firm value, there are several studies showing firms with stronger corporate governance to be associated with higher firm value (for an overview, see Ammann et al., 2011). The rational being that firms with weaker governance face greater agency problems and thus more value-destroying behavior (Core et al., 1999).

We argue that if director election results are informative of a director's abilities to monitor and advise management, we expect directors receiving less shareholder support to have a negative impact on firm performance. Particularly, we focus on the impact of directors receiving significantly less shareholder support compared to their peers: *unwanted directors*. We assume the main information in receiving less votes than their peers is that they are less effective monitors and/or advisors in the eyes of shareholders. Using multiple measures based on voting outcomes to define *unwantedeness*, we find an association between the number of unwanted directors on a firm's board and a decline in subsequent firm performance – both in terms of stock market and operating performance. A one unit increase in the number of unwanted directors on a firm's board is on average associated with a decline in subsequent stock performance by 37 basis points p.a. and a decline in operating performance by 39 basis points p.a. The results hold when controlling for a variety of firm characteristics, board characteristics and takeover defense mechanisms as well as when including various fixed effects.

We also find evidence suggesting that firm performance is not negatively affected when there is only one unwanted director on a firm's board, however, having two or more unwanted directors on the board is associated with a decline in subsequent firm performance. Furthermore, we analyze if markets differentiate between unwanted directors who stayed unwanted, i.e. directors receiving significantly less shareholder support at two consecutive elections, and those who only receive significantly less shareholder support in one respective year. The results suggest that unwanted directors who stayed unwanted are not significant to subsequent stock market performance indicating that markets already account for unwantedeness when it first appears. Overall, our first set of results supports the view of shareholder voting outcomes being informative of the level and the effectiveness of monitoring and advising exerted by corporate directors.

To address concerns of endogeneity (Hermalin and Weisbach, 2003), we follow Nguyen and Nielsen (2010) by analyzing stock price reactions surrounding the sudden deaths of corporate directors. A major advantage of using this approach is that sudden deaths occur randomly and are independent of firm and board characteristics. Hence, this approach helps us to confirm a relationship between an individual director's voting results and firm value. Our results show both the percentage "for" votes a particular director receives as well as our definitions of unwanted directors to be statistically significantly related to the stock market reaction surrounding the sudden deaths. We find stock price reactions to sudden deaths of directors who receive more shareholder support to be more negative, while we find stock price reactions to sudden deaths of unwanted directors to be more positive. Thus, the results support our previous findings. Additionally, we use four different pair trading strategies based on stocks of firms with and without unwanted directors to confirm our previous findings. We show selling stocks of firms with a share of more than 60% of unwanted directors and buying equivalent firms without any unwanted directors on the board to earn an average return of 5.91% p.a. Since the number of unwanted directors on the firm's board matters, we find strategies focusing on firms with a smaller share of unwanted directors to be still profitable, but less so. To ensure that the results are not driven by riskiness or "style" factors, we run various regressions using the most common factors proposed in the literature (see e.g. Carhart, 1997; Fama and French, 1995, 2015) as independent variables. The results are consistent with what we found before. So the strategies focusing on firms with a share of more than 60% of unwanted directors on the board and equivalent firms earn a significant monthly alpha of at least 52 basis points.

4.2 Literature Review

This paper contributes to the literature in several ways. First, we contribute to the literature on director elections in the US. In this regard, Cai et al. (2009) were the first to study a large sample of director elections. Using election events at Russell 3000 firms between 2003 and 2005, they show that there is generally strong support for corporate directors; and that votes are mainly related to ISS recommendations and meeting attendance. Ertimur et al. (2018) document similar results analyzing a sample of uncontested director election events at S&P 500 firms between 2003 and 2010. However, although both studies highlight a relation between shareholder votes and subsequent corporate governance changes (e.g. removal of poison pills and classified boards), they do not find a relationship between election results and consequences for individual directors. In contrast, Aggarwal et al. (2019) find a relation between dissent votes and negative consequences for the respective directors. For instance, they show directors facing shareholder dissent to be not only more likely to lose their board seat and to be removed from important board committees, but also to be more likely to face reduced opportunities for additional board seats at other companies. They attribute the different results to the larger sample they use for their analysis. The findings of Fos et al. (2018) also support the view that director elections matter and that directors care about the reputational effect of election results. According to their findings, the proximity to director elections has an important impact on CEO turnover-performance sensitivity. In a recent study, Chen and Guay (2018) provide evidence of busy directors receiving significantly less "for" votes. Thus, they underline that shareholders voice their opinion using their votes.

We extend this strand of literature by specifically shedding light on the relationship between outcomes at director elections and firm performance. Regarding this aspect, the evidence from prior studies is limited. While Fischer et al. (2009) show stock price reactions to announcements of management turnover to be related to voting approval, Cai et al. (2009) do not find director election results to be related to subsequent firm performance. Ertimur et al. (2018), who study the responsiveness of firms to shareholder dissent, also conclude that firm performance between responding and non-responding firms does not differ significantly. However, using a sample of director election events at Russell 3000 firms between 2001 and 2018, we show outcomes at director elections to be associated with subsequent firm performance. In particular, we find evidence that boards with unwanted directors are associated with a decrease in subsequent firm performance (both in terms of operating and stock performance). We also show the number of unwanted directors on the board to be the predominant driver.

Regarding the latter, we also contribute to the literature on the influence of boards on firm performance. There are several recent studies showing that boards and more particularly board composition influences firm performance and its variability (see e.g. Bernile et al., 2018; Duchin et al., 2010; Frijns et al., 2016; Hauser, 2018; Souther, 2019; Tran and Turkiela, 2020). Aspects discussed in prior research include inter alia board independence, board diversity, board structure, and board busyness. For instance, Duchin et al. (2010) use regulatory changes as exogenous shocks to show the value-impact of forcing a board to adopt a composition other than which it had endogenously chosen. Besides, Renjie and Verwijmeren (2019) show firms with distracted directors to have inactive boards and experience a significant decline in firm value. Our findings deepen the understanding of the role of the board of directors on firm performance by showing that particularly the sum of unwanted directors on a board is negatively associated with subsequent firm performance.

Our study also relates to the literature examining the value of individual corporate directors. There are several studies using (sudden) deaths to analyze the value of corporate directors (see e.g. Drobetz et al., 2018; Falato et al., 2014; Fedaseyeu et al., 2018; Nguyen and Nielsen, 2010; Von Meyerinck et al., 2016). Their findings suggest that directors have an important impact on firm value depending on certain director characteristics. For instance, directors who are independent, have specific industry expertise, or have general expertise seem to have a positive impact on firm value, while busy directors seem to destroy firm value. In a more recent paper, Burt et al. (2020) take a different approach to estimate the influence of directors on firm value. By analyzing the commonality in idiosyncratic returns of firms which share a director, they provide evidence of an individual director influencing firm value by up to 1%. We extend this strand of literature since we also use sudden deaths as a robustness check to show that the sudden deaths of unwanted directors are associated with a positive market reaction; thus influencing firm value. Further, we attempt to identify director characteristics, which cause shareholders to withhold votes from the election of these unwanted directors.

Finally, our study contributes to the literature on the director labor market and the selection of individual directors. While directors should ideally be nominated to independently advise and monitor management (Coles et al., 2008), there is also evidence suggesting that CEOs influence the selection of directors in order to weaken board monitoring (Shivdasani and Yermack, 1999). Although Becher et al. (2017) stress that shareholders typically have little influence in the nomination process, they find that boards nominate directors in order to address changing needs for advising and monitoring. Denis et al. (2018) also find that boards select directors based on their qualifications and expertise. Our findings, however, suggest that the director nomination process might be suboptimal. Shareholders seem to anticipate whether directors contribute to shareholder value and use their votes to address this issue. In this respect, it also remains to be seen whether the increasing use of proxy access (among S&P 500 firms) might enhance the director-firm matching in the future (Sidley Austin, 2020). This regulation, which was introduced in the Dodd-Frank Act, gives certain shareholders the right to include a limited number of their own director candidates on the company's proxy sheet. This might provide serious competition for incumbent directors.

The remainder of this paper is structured as follows. Section 4.3 presents the dataset, the variable constructions and summary statistics, while Section 4.4 proceeds with the empirical analysis. Section 4.5 contains robustness tests using sudden death cases and a trading strategy based on our measure of unwantedness. The final section concludes.

4.3 Data

4.3.1 Data Sources and Sample Selection

We use a U.S. panel of directors that comprises data on director characteristics, CEO characteristics, shareholder voting, firm characteristics, takeover defense mechanisms and stock returns. Our main data source is the MSCI GMI Ratings database which covers S&P 1500 firms for the period from 2001 to 2018, Russell 1000 firms for the period from 2002 to 2005 and Russell 3000 firms for the period from 2006 to 2018. This dataset provides data on director characteristics, CEO characteristics, and takeover defense mechanisms. We obtain director-level voting data from the ISS Voting Analytics U.S. database, which provides voting results from shareholder meetings of Russell 3000 firms starting in the year 2003. We hand-collect additional voting data on S&P 1500 firms for the missing years 2001 and 2002. The ISS dataset additionally provides information on a firm's cusip, ticker, shareholder meeting dates and on the ISS voting recommendations for each year and director.

We merge the director data obtained from the MSCI GMI Ratings database and the voting data from ISS using a fuzzy matching algorithm applied to the name and surname of each director, which are available in both datasets. To ensure a high level of matching quality, we match both datasets iteratively in order to considerably reduce the number of observations matched in each step. For a match, we require the tickers to be equal and that the shareholder meeting (date included in the ISS Voting Analytics dataset) took place within a window of 180 days after the proxy filing was disclosed (date included in the MSCI GMI Ratings dataset). To further increase matching quality, we require the fuzzy matching score to be > 80. Only if these conditions are met, we include a match in our final dataset.

We merge the matched director and voting data with firm-level data from the merged CRSP/Compustat database (accounting and stock price data) as well as with ownership information directly taken from the form 13D filings, both on an annual level. We further derive board characteristics from the MSCI GMI Ratings database by simply aggregating the relevant variables on firm-level.

Overall, our final sample consists of 191,126 director-level observations for the period from 2001 to 2018. In particular, data on *for votes* and the ISS recommendation are available for all observations. Further, we aggregate director-level data for each firm resulting in data for 30,564 firm-year observations. For each of these observations, information on all control variables is available.

4.3.2 Key Variables

The main variable we use to construct our measures of unwantedness is *percentage (%) for votes* which we calculate for each director in our dataset in line with the literature (Cai et al., 2009) as the faction of *for votes* divided by the sum of all votes cast (*for votes + withhold votes + against votes*). We explicitly include *against votes* to account for majority voting. In case of plurality voting, *against votes* takes the value of zero.

We construct two different dummy variables on director-level using *%-for votes*. The dummy variable *unwanted dir., 25%*$_{(y,i)}$ takes the value of one if a particular director receives less *%-for votes* than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification), and zero otherwise. The dummy variable *unwanted dir., 10%*$_{(y,i)}$ is constructed similarly using the 10$^{\text{th}}$ percentile as a cut-off level. By using these definitions, we aim to achieve two goals. First, we aim to define an *unwanted* director as a director who receives significantly less *%-for votes* than her peers in the same year and industry. Thus, we already control for any year-fixed and industry-fixed effects within our two measures. Second, we deliberately do not use "excess" votes as defined in Cai et al. (2009). Subtracting the election's mean *%-for votes* from *%-for votes* would eliminate the comparability on the director-level as we would not account for a certain level of *%-for votes* on the company-level. Additionally, our definition of unwantedness enables us to shed light on insightful measures on the firm-level.

We also define measures of unwantedness on firm-level. The variables $\sum$*(unwanted dir., 25%*$_{(y,i)}$*)* and $\sum$(unwanted dir., 10%$_{(y,i)}$) are defined as the sum of directors on a firm's board receiving less *%-for votes* than the 25$^{\text{th}}$ (10$^{\text{th}}$) percentile in the respective year and industry. Moreover, we define $\sum$*(unwanted dirs., 25%*$_{(y,i)}$*, stayed)* as the sum of directors on a firm's board who not only receive less *%-for votes* than the 25$^{\text{th}}$ percentile in the respective year and industry, but also received less *%-for votes* than the 25$^{\text{th}}$ percentile in the prior year. The variable $\sum$*(unwanted dirs., 25%*$_{(y,i)}$*), new)*, however, is defined as the sum of directors on a firm's board who only receive less *%-for votes* than the 25$^{\text{th}}$ percentile in the respective year and industry. The variables $\sum$*(unwanted dirs., 10%*$_{(y,i)}$*, stayed)* and $\sum$*(unwanted dirs., 10%*$_{(y,i)}$*, new)* are defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level.

4.3.3 Summary Statistics

Table 4.1: This table presents summary statistics for director characteristics, ISS recommendations, *%-for votes* and our definitions of *unwanted* directors (discussed in Section 4.3.2) using a sample of director election events from 2001 to 2018. More details on the construction of the sample are discussed in Section 4.3.3. All variables are defined in Appendix 4.B.

	Obs.	Mean	10$^{\text{th}}$	25$^{\text{th}}$	50$^{\text{th}}$	Std.
Outside director	191,126	0.85				
Attendance	191,126	0.01				
Problem director	191,126	0.03				
Director ownership	191,126	3492.64	0.00	7.71	135.77	14259.26
Director tenure	191,126	7.94	1.00	3.00	6.00	7.17
Director age	191,126	60.38	48.00	54.00	61.00	9.10
Director gender	191,126	0.87				
Busy director	191,126	0.18				
Any CEO	191,126	0.12				
Founder	191,126	0.02				
Company CEO	191,126	0.02				
Military	191,126	0.01				
Professor	191,126	0.01				
Ph.D	191,126	0.03				
Committee lead	191,126	0.14				
Committee non chair	191,126	0.48				
ISS recommendation	191,126	0.91				
%-for votes	191,126	0.95	0.87	0.95	0.98	0.08
unwanted dir., 25%$_{(y,i)}$	191,126	0.25				
unwanted dir., 10%$_{(y,i)}$	191,126	0.10				
unwanted dir., 25%$_{(y,i)}$**, stayed**	191,126	0.07				
unwanted dir., 10%$_{(y,i)}$**, stayed**	191,126	0.02				

Table 4.1 shows summary statistics on director-level. The average director in our sample is 60.38 years old and has a tenure period of 7.94 years. Moreover, 87% of the directors are male. 85%

of the directors in our panel are outside directors and 18% are classified as busy directors. We further find that 12% of the directors serve as a CEO of another company, while 2% are the respective company's CEO. 48% of the directors serve on one of the board's committees and 14% even serve as the chairman of one of these committees. Regarding variables related to a director's voting results, we find that *%-for votes* has a mean of 95% and a median of 98%. These numbers are not only almost identical to the ones reported in Cai et al. (2009) but also indicate directors generally receiving strong shareholder support. Further, we find 7% of all directors to receive less *%-for votes* than the 25th percentile (2% to receive less *%-for votes* than the 10th percentile) in two consecutive years. Other variables indicate that only 1% of directors failed attendance (have attended less than 75% of all meetings within a year) and 3% are classified as problem directors (directors who were on the boards of companies that failed, were involved in scandals or awarded CEOs with excessive pay packages).

Table 4.2: This table presents summary statistics for firm characteristic, takeover defense mechanisms as well as board characteristics using a sample of firm-year observations for the period from 2001 to 2018. More details on the sample construction are discussed in Section 4.3.3. All variables are defined in Appendix 4.B.

	Obs.	Mean	10th	25th	50th	Std.
Firm age	31,836	21.22	4.01	9.02	17.04	15.61
ln**(Firm age)**	31,836	2.83	1.61	2.30	2.89	0.78
Firm size	31,836	10794.30	203.79	515.35	1727.14	38520.21
ln**(Firm size)**	31,836	7.53	5.32	6.25	7.45	1.76
B&h returns	31,836	0.10	-0.39	-0.15	0.07	0.44
Stock volatility	31,836	0.41	0.20	0.25	0.35	0.22
ROE	31,836	0.04	-0.23	0.02	0.08	0.47
Leverage	31,836	0.58	0.22	0.39	0.57	0.26
Tobin's Q	31,836	1.89	0.96	1.06	1.41	1.31
CapEx	31,836	0.04	0.00	0.01	0.02	0.05
R&D	31,836	0.04	0.00	0.00	0.00	0.08
Active ownership	31,836	0.15	0.00	0.00	0.06	0.22
Classified board	31,836	0.19				
Business combination provision	31,689	0.62				
Constituency provision	31,689	0.25				
Cumulative voting	31,689	0.17				
Dual class stock	31,689	0.08				
Fair price provision	31,689	0.35				
Poison pill	31,689	0.17				
Shareholder fill vacancy	31,689	0.47				
Board size	31,836	9.40	6.00	8.00	9.00	2.60
ln**(Board Size)**	31,836	2.31	1.95	2.20	2.30	0.25
Board age	31,836	59.17	52.50	56.00	59.50	4.98
Board tenure	31,836	6.46	2.00	4.00	6.00	3.68
Board outside directors	31,836	7.18	4.00	6.00	7.00	2.28

Table 4.2 reports summary statistics for our control variables on firm-level grouped by firm characteristics, takeover defense mechanisms, and board characteristics. However, takeover defense mechanisms are missing in the panel for 147 firm-year observations. The average firm in our sample holds total assets worth 10794.30 million US$ and is 21.22 years old. Further, firms in our sample have an annual median stock return of 7% and an annual median stock return volatility of 35%. The average *Leverage* is 58% and average *Tobin's Q* is 1.89. *CapEx* and *R&D*

expenses (both scaled by total assets) are 4% on average. Mean active ownership (as reported in the latest 13D filing by the end of the fiscal year) is 15%, showing a heavily left-skewed distribution.

It turns out that *Business combination provisions* (62%), *Shareholder fill vacancy* (47%), and *Fair price provision* are the most prevalent takeover defense mechanisms. *Cumulative voting* (17%), *Poison pill* (17%), and *Dual class stock* (8%) are used less heavily. The average *Board size* of 9.4 directors is identical with the board size reported in Cai et al. (2013). The numbers on *Board age*, *Board tenure*, and *Outside directors* on a firm's board are also similar to those reported in previous studies.

4.4 Results

4.4.1 Determinants of For Votes

Following Cai et al. (2009), we first look at the determinants of a director's individual election outcomes using our sample of election events at Russell 3000 firms spanning over 17 years. To do so, we perform ordinary least squares (OLS) regressions where the dependent variable is *%-for votes*. Independent variables include firm, board and director characteristics. Moreover, we follow Cai et al. (2009) by including the variable *ISS estimation*, which is based on the residuals from a logit regression explaining the ISS recommendation with various firm, board, and director characteristics. The results from our OLS regressions are presented in Table 4.3.

We report the results from the logit regression explaining the ISS recommendation in Table 4.15 in the Appendix. We estimate both regressions (columns (1) and (3)) using year-fixed effects. Column (1) reports the results using firm-fixed effects additionally and column (3) using industry-fixed effects. Columns (2) and (4) report the marginal effects respectively. In line with the results from Cai et al. (2009), we find that a positive ISS recommendation is less likely when buy & hold returns are lower and stock volatility higher, both with a coefficient significant at the 1% level. Regarding the characteristics of directors, we find that a positive recommendation is less likely for men, busy directors, directors who attended less than 75% of all board meetings in the prior year, and with increasing length of tenure. In contrast, a positive ISS recommendation is more likely for older directors and outside directors. For all of the above mentioned director characteristics, the coefficient is significant at the 1% level regardless of the specification used.

Table 4.3: This table reports the results from OLS regressions where the dependent variable is *%-for votes*, which is calculated as the "for" votes a particular director receives divided by the the sum of all votes cast at the election. Independent variables include firm, board and director characteristics. Following Cai et al. (2009), we also include the residuals from a logistic regression, where the ISS recommendation is explained by various firm, board and director characteristics, as a further control variable named *ISS estimation*. All variables are defined in Appendix 4.B. In columns (1) to (3), we report the results for the full sample. All specifications include year-fixed effects. We also include firm-fixed effects in column (1), industry-fixed effects based on Fama and French's 48 industry classification in column (2), and firm and director-fixed effects in column (3). In columns (4) to (6), we report the results for a subsample where we exclude directors receiving less *%-for votes* than the 25^{th} percentile in the respective year. The specifications, however, are similar to the previous columns. Across all columns, standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	%-for votes					
Observations	191,126	191,126	191,126	159,368	159,368	159,368
R^2	0.4110	0.3820	0.4113	0.3597	0.3356	0.3738
R^2 **(Within)**	0.4153	0.3861	0.4149	0.3659	0.3418	0.3785
F-statistic	4344.5	3936.7	5802.3	2903.6	2681.7	4133.9
p**-value (F-stat)**	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Intercept	0.9601***	0.9240***	0.0000**	0.9630***	0.9449***	0.0000
	(0.0000)	(0.0000)	(0.0497)	(0.0000)	(0.0000)	(0.9885)
ln**(Firm age**$_{t-1}$**)**	-0.0009	0.0003	-0.0020**	0.0003	0.0000	-0.0014*
	(0.4545)	(0.8007)	(0.0368)	(0.8229)	(0.9451)	(0.0967)
ln**(Firm size**$_{t-1}$**)**	-0.0012	0.0024***	0.0010*	-0.0010	0.0020***	0.0004
	(0.1551)	(0.0000)	(0.0638)	(0.2571)	(0.0001)	(0.3638)
B&h returns$_{t-1}$	0.0078***	0.0070***	0.0074***	0.0079***	0.0077***	0.0077***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Stock vola.$_{t-1}$	-0.0152***	-0.0204***	-0.0183***	-0.0182***	-0.0232***	-0.0201***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tobin's Q$_{t-1}$	0.0024***	0.0026***	0.0031***	0.0025***	0.0022***	0.0027***
	(0.0000)	(0.0013)	(0.0000)	(0.0000)	(0.0012)	(0.0000)
Leverage$_{t-1}$	-0.0075***	0.0025	-0.0023	-0.0085***	0.0012	-0.0046**
	(0.0092)	(0.4588)	(0.3399)	(0.0030)	(0.6890)	(0.0429)
ROE$_{t-1}$	0.0026**	0.0031***	0.0025**	0.0026**	0.0031***	0.0024**
	(0.0104)	(0.0006)	(0.0120)	(0.0121)	(0.0003)	(0.0217)
CapEx$_{t-1}$	0.0248	0.0184	0.0166**	0.0198	0.0201	0.0083
	(0.1442)	(0.2599)	(0.0124)	(0.2116)	(0.2144)	(0.1684)
R&D$_{t-1}$	-0.0443***	-0.0036	-0.0187	-0.0472***	-0.0030	-0.0216*
	(0.0002)	(0.7547)	(0.1185)	(0.0000)	(0.7699)	(0.0720)
ln**(Board size)**	0.0089***	0.0167***	0.0097***	0.0064**	0.0107***	0.0070***
	(0.0028)	(0.0001)	(0.0000)	(0.0236)	(0.0080)	(0.0002)
Board age	-0.0000	-0.0004***	-0.0003***	0.0000	-0.0004***	-0.0003***
	(0.9831)	(0.0048)	(0.0073)	(0.9829)	(0.0009)	(0.0099)
Board tenure	-0.0004**	0.0000	0.0000	-0.0004***	-0.0000	-0.0000
	(0.0267)	(0.9960)	(0.7946)	(0.0086)	(0.5974)	(0.6541)
Active ownership	0.0037	0.0020	0.0054**	0.0019	-0.0005	0.0032
	(0.4876)	(0.4848)	(0.0284)	(0.7030)	(0.8642)	(0.1628)
Outside director	-0.0023***	-0.0016	-0.0036***	-0.0002	0.0010	-0.0006
	(0.0033)	(0.4498)	(0.0004)	(0.8158)	(0.5574)	(0.4945)
Attendance	-0.1059***	-0.1032***	-0.1100***	-0.0659***	-0.0619***	-0.0715***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Problem dir.	-0.0026***	-0.0033***	0.0005	-0.0014	-0.0028***	0.0029*
	(0.0085)	(0.0023)	(0.7483)	(0.1031)	(0.0065)	(0.0872)
Dir. ownership	-0.0000	0.0000	0.0000***	-0.0000	-0.0000	0.0000
	(0.9672)	(0.3238)	(0.0058)	(0.2906)	(0.5902)	(0.3586)
Dir. tenure	-0.0011***	-0.0010***	-0.0007***	-0.0008***	-0.0008***	-0.0006***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Dir. age	0.0000***	0.0000**	0.0005***	0.0000***	0.0000**	0.0008***
	(0.0001)	(0.0113)	(0.0002)	(0.0001)	(0.0106)	(0.0000)
Dir. gender	-0.0040***	-0.0054***		-0.0026***	-0.0038***	
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	
Busy dir.	-0.0084***	-0.0074***	-0.0042***	-0.0045***	-0.0037***	-0.0026***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0003)
Any CEO	0.0016***	0.0012	-0.0014*	0.0013**	0.0010	-0.0015**
	(0.0087)	(0.2671)	(0.0911)	(0.0193)	(0.2606)	(0.0397)
Founder	-0.0010	-0.0040		-0.0014	-0.0039*	
	(0.5413)	(0.1141)		(0.3502)	(0.0929)	
Company CEO	0.0038***	0.0061***	-0.0009	0.0037***	0.0061***	-0.0004
	(0.0002)	(0.0010)	(0.4293)	(0.0001)	(0.0000)	(0.7839)
Military	0.0063***	0.0079***		0.0052***	0.0066**	
	(0.0008)	(0.0035)		(0.0009)	(0.0101)	
Professor	0.0002	-0.0002		-0.0000	0.0000	
	(0.9317)	(0.9519)		(0.9840)	(0.9898)	
Ph.D.	-0.0012	-0.0024**		-0.0006	-0.0014	
	(0.1741)	(0.0254)		(0.5217)	(0.1393)	
C. lead	-0.0034***	-0.0024***		-0.0020***	-0.0005	
	(0.0000)	(0.0000)		(0.0000)	(0.3049)	
C. Non chair	-0.0018***	-0.0020***		-0.0015***	-0.0015***	
	(0.0000)	(0.0000)		(0.0002)	(0.0041)	
ISS estimation	0.1738***	0.1651***	0.1880***	0.1556***	0.1492***	0.1741***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Year FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	no	no	yes	no	no
Industry FE	no	yes	yes	no	yes	yes
Director FE	no	no	yes	no	no	yes

In the table above, we report the results from the OLS regressions explaining *%-for votes*. In columns (1) to (3), the regressions are based on our full sample. Overall, the results are qualitatively similar to those reported in Cai et al. (2009). We also find that the ISS recommendation and meeting attendance play a significant role in determining a director's election outcomes regardless of whether we control for firm and year-fixed effects (column (1)), industry and year-fixed effects (column (2)) or firm, director and year-fixed effects (column (3)). Moreover, we find a positive relation between the firm's performance in the prior fiscal year and the *%-for votes* a director receives. Also, busy directors and more tenured directors are associated with less shareholder support.

In contrast to Cai et al. (2009), the coefficients on the variable *Dir. gender*, which is equal to one if the director is male and zero otherwise, are negative and statistically significant. The coefficients' magnitude implies that male directors receive on average 0.5% less *%-for votes* than female directors. Additionally, it is noteworthy that we also find positive and statistically significant coefficients on the variable *Military* (0.83% higher *%-for votes*). Hence, this suggests directors with a military background to receive more shareholder support at director elections.

In columns (4) to (6) we report the results from the same regressions based on a subsample where we exclude directors receiving less *%-for votes* than the 25$^{\text{th}}$ percentile in the respective year. The rationale behind using this subsample is to ensure that the results are not driven by directors receiving significantly less shareholder support. However, the results do not change qualitatively.

We also check whether the aforementioned results, particularly regarding the director-specific characteristics, are robust to using the *excess votes* a particular director receives as the dependent variable. We also perform the same regressions using the variable *excess votes excl. lowest* as the dependent variable. This variable is defined as the *%-for votes* a particular director receives minus the company's average at the election excluding the director with the lowest *%-for votes*. Table 4.16 in the Appendix reports the results from these regressions. All specifications are similar to those in Table 4.3.

As expected, we also find that busy directors, male directors and more tenured directors receive significantly less "excess" votes at elections. Besides, we find further evidence suggesting that directors with a military background receive significantly more shareholder support (p-value < 0.01).

4.4.2 Determinants of Unwantedness

Next, we investigate the determinants of unwanted directors. Therefore, we run logit regressions where the dependent variable is either the dummy variable *d(unwanted dir., 25%*$_{(y,i)}$*)* or the dummy variable *d(unwanted dir., 10%*$_{(y,i)}$*)*. Independent variables include firm, board and director characteristics as well as the residuals from logit regressions explaining the ISS recommendation. We present the results in Table 4.4.

In columns (1) and (3), we report the results from the regressions where the dependent variable is *d(unwanted dir., 25%*$_{(y,i)}$*)*. Columns (2) and (4) show the marginal effects from these regressions respectively. Both regressions include year-fixed effects. Additionally, we include firm-fixed effects in column (1) and firm and director-fixed effects in column (3). Throughout the two specifications and the marginal effects, we find that becoming an unwanted director is less likely at firms with good prior-year performance, low leverage and low stock volatility. Also, becoming an unwanted director is less likely at firms with larger boards. In terms of director characteristics, we find that more tenured and male directors as well as directors with a PhD are more likely to become an unwanted director, whereas directors with a military background are less likely to become an unwanted director. Moreover, being the chairman of a board committee is associated with a higher probability of becoming an unwanted director, while being the firm's CEO or founder or even the CEO of another company is associated with a lower probability of becoming an unwanted director. However, in line with the findings from Cai et al. (2009), the magnitude of the aforementioned variables' coefficients is small compared to the coefficients on the variables *Attendance* and *ISS estimation*. Hence, these two variables are the most important in determining whether a director becomes an unwanted director. The positive sign of the coefficient on *Attendance* implies that directors, who fail to meet 75% of board meetings, are more likely to be unwanted by shareholders, while the the negative sign on *ISS estimation* implies that directors with a "for" recommendation by the ISS are less likely to be unwanted by shareholders.

In columns (5) to (8), we show the results from the same regressions as well as the marginal effects where the dependent variable is *d(unwanted dir., 10%*$_{(y,i)}$*)*. Although the results are similar to those found in columns (1) to (4), there are a few exceptions. For instance, we do not find statistically significant coefficients on the variable *Stock vola*$_{t\text{-}1}$. Additionally, we do not find statistically significant coefficients on *ROE*$_{t\text{-}1}$ and *CapEx*$_{t\text{-}1}$ across all columns.

Table 4.4: This table reports the results from logit regressions where the dependent variable in columns (1) and (3) is the dummy variable *unwanted dir., 25%*$_{(y,i)}$ and the dependent variable in columns (5) and (7) is the dummy variable *unwanted dir., 10%*$_{(y,i)}$. In columns (2) and (4) as well as (6) and (8), we report the marginal effects based on the respective logit regression. The dummy variable *unwanted dir., 25%*$_{(y,i)}$ equals one if the particular director receives less *%-for votes* than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification), and zero otherwise. The dummy variable *unwanted dir., 10%*$_{(y,i)}$ is defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level. Independent variables include firm, board and director characteristics. Following Cai et al. (2009), we also include the residuals from a logistic regression, where the ISS recommendation is explained by various firm, board and director characteristics, as a further control variable named *ISS estimation*. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (5) and firm and director-fixed effects in columns (3) and (6). Across all specifications, standard errors are clustered by firm. Robust *p*-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Variable	25% year, industry				10% year, industry			
Observations	191,126	191,126	191,126	191,126	191,126	191,126	191,126	191,126
	Logit	$\partial y/\partial x$	Logit	$\partial y/\partial x$	Logit	$\partial y/\partial x$	Logit	$\partial y/\partial x$
Pseudo-R^2	0.1283		0.0786		0.2459		0.1793	
Intercept	-1.1955***		-1.1591***		-2.6247***		-2.4810***	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
ln(**Firm age**$_{t-1}$)	0.0363	0.0058	0.2242***	0.0382***	0.1624**	0.0109**	0.2944***	0.0216***
	(0.6768)	(0.6760)	(0.0075)	(0.0070)	(0.0112)	(0.0110)	(0.0011)	(0.0010)
ln(**Firm size**$_{t-1}$)	0.0328	0.0052	0.0460	0.0078	0.0889**	0.0060**	0.0923*	0.0068*
	(0.4919)	(0.4910)	(0.2370)	(0.2360)	(0.0309)	(0.0310)	(0.0666)	(0.0690)
B&h returns$_{t-1}$	-0.2116***	-0.0335***	-0.1924***	-0.0327***	-0.1812***	-0.0122***	-0.1608***	-0.0118***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)
Stock vola$_{t-1}$	0.5403***	0.0857***	0.6304***	0.1073***	0.1788	0.012	0.2825*	0.0208*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2573)	(0.2560)	(0.0581)	(0.0580)
Tobin's Q$_{t-1}$	-0.1275***	-0.0202***	-0.1257***	-0.0214***	-0.0887***	-0.0060***	-0.1093***	-0.0080***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0015)	(0.0010)	(0.0002)	(0.0000)
Leverage$_{t-1}$	0.6112***	0.0969***	0.4902***	0.0834***	0.5298***	0.0357***	0.4393***	0.0323***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0047)	(0.0050)
ROE$_{t-1}$	-0.0989***	-0.0157***	-0.0926***	-0.0158	-0.0577	-0.0039	-0.0379	-0.0028
	(0.0060)	(0.0060)	(0.0097)	(0.0100)	(0.3006)	(0.3010)	(0.4919)	(0.4920)
CapEx$_{t-1}$	-0.9507*	-0.1508*	-0.8518*	-0.1450*	-0.4628	-0.0312	-0.3470	-0.0255
	(0.0698)	(0.0710)	(0.0950)	(0.0960)	(0.4714)	(0.4710)	(0.6163)	(0.6160)
R&D$_{t-1}$	1.1152*	0.1768*	1.4717***	0.2505***	1.2883	0.0867	1.6579*	0.1219
	(0.0728)	(0.0710)	(0.0013)	(0.0010)	(0.1334)	(0.1310)	(0.0533)	(0.0500)
ln(**Board size**)	-0.3248**	-0.0515	-0.2355**	-0.0401**	-0.3440**	-0.0232**	-0.1891	-0.0139
	(0.0104)	(0.0100)	(0.0159)	(0.0160)	(0.0110)	(0.0110)	(0.1767)	(0.1770)
Board age	0.0019	0.0003	0.0023	0.0004	0.0054	0.0004	0.0121*	0.0009*
	(0.7161)	(0.7160)	(0.6437)	(0.6440)	(0.5203)	(0.5190)	(0.0975)	(0.0970)
Board tenure	0.0098*	0.0015*	0.0063	0.0011	0.0032	0.0002	-0.0043	-0.0003
	(0.0951)	(0.0960)	(0.2522)	(0.2530)	(0.7023)	(0.7020)	(0.6065)	(0.6070)
Active owners.	-0.1218	-0.0193	-0.1695	-0.0289	-0.2294	-0.0154	-0.2345	-0.0172
	(0.5110)	(0.5110)	(0.2920)	(0.2920)	(0.3791)	(0.3800)	(0.3881)	(0.3890)
Outside dir.	-0.0541*	-0.0086*	0.0263	0.0045	0.1457***	0.0098***	0.1669***	0.0123***
	(0.0630)	(0.0630)	(0.5170)	(0.5170)	(0.0020)	(0.0020)	(0.0045)	(0.0040)
Attendance	1.9564***	0.3102***	2.0023***	0.3408***	2.2233***	0.1497***	2.5108***	0.1846***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Problem dir.	0.1383***	0.0219***	0.0263	0.0045	0.1380**	0.0093**	-0.0193	-0.0014
	(0.0012)	(0.0010)	(0.7524)	(0.7520)	(0.0208)	(0.0210)	(0.8844)	(0.8840)
Dir. owners.	-0.0000	-0.0000	-0.0000**	-0.0000**	-0.0000*	-0.0000*	-0.0000***	-0.0000***
	(0.3531)	(0.3530)	(0.0427)	(0.0420)	(0.0941)	(0.0950)	(0.0042)	(0.0040)
Dir. tenure	0.0434***	0.0069***	0.0329***	0.0056***	0.0380***	0.0026***	0.0252***	0.0019***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Dir. age	-0.0036***	-0.0006***	0.0103**	0.0018**	-0.0035***	-0.0002***	0.0079	0.0006
	(0.0001)	(0.0000)	(0.0198)	(0.0200)	(0.0078)	(0.0080)	(0.1792)	(0.1790)
Dir. gender	0.1605***	0.0255***	0.2094***	0.0356***	0.1769***	0.0119***	0.1678***	0.0123***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Busy dir.	0.3508***	0.0556***	-0.0427	-0.0073	0.3432***	0.0231***	-0.0197	-0.0014
	(0.0000)	(0.0000)	(0.2131)	(0.2130)	(0.0000)	(0.0000)	(0.7000)	(0.7000)
Any CEO	-0.1347***	-0.0214***			-0.1193***	-0.0080***		
	(0.0000)	(0.0000)			(0.0016)	(0.0020)		
Founder	-0.1763***	-0.0280***			-0.0710	-0.0048		
	(0.0011)	(0.0010)			(0.3907)	(0.3910)		
Firm CEO	-0.1677***	-0.0266***	0.0520	0.0088	-0.3435***	-0.0231***	-0.1217	-0.0089
	(0.0006)	(0.0010)	(0.3330)	(0.3330)	(0.0000)	(0.0000)	(0.1115)	(0.1120)
Military	-0.2001**	-0.0317**			-0.4219**	-0.0284**		
	(0.0235)	(0.0240)			(0.0138)	(0.0140)		
Professor	-0.0237	-0.0038			-0.0950	-0.0064		
	(0.7550)	(0.7550)			(0.3553)	(0.3550)		
Ph.D.	0.0959***	0.0152***			0.0644	0.0043		
	(0.0073)	(0.0070)			(0.1980)	(0.2000)		
C. lead	0.1183***	0.0188***			0.0655**	0.0044**		
	(0.0000)	(0.0000)			(0.0168)	(0.0170)		
C. non chair	0.0194	0.0031			0.0426*	0.0029*		
	(0.2648)	(0.2640)			(0.0753)	(0.0750)		
ISS estimation	-3.3417***	-0.5299***	-3.3085***	-0.5631***	-4.0953***	-0.2757***	-4.4522***	-0.3273***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	no	no	no	no	no	no	no	no
Director FE	no	no	yes	yes	no	no	yes	yes

With respect to director characteristics, statistical significance also vanishes on the variables *Founder* and *PhD*. In contrast to columns (1) to (4), the results, however, indicate outside directors to be more likely to become unwanted. Despite these differences, the results, nonetheless, stress that attendance at board meetings and the ISS voting recommendation are the most important determinants of unwanted directors.

In the Appendix, we also show the results from OLS regressions where the dependent variable is *%-for votes* and where we interact all independent variables with our two dummy variables *d(unwanted dir., 25%$_{(y,i)}$)* and *d(unwanted dir., 10%$_{(y,i)}$)* (Table 4.17). Except for a few minor differences, the results overall support the findings from the logit regressions presented above.

4.4.3 Firm Performance

In this section, we investigate whether the number of unwanted directors on a firm's board has an impact on subsequent firm performance – both in terms of stock market and operating performance. To do so, we start by performing Fama-MacBeth regressions of the buy-and-hold returns (*B&h returns*) on the sum of unwanted directors. Specifically, we use our measures $\sum$*(unwanted dir., 25%$_{(y,i)}$)* and $\sum$*(unwanted dir., 10%$_{(y,i)}$)*, which are defined as the sum of directors on the firm's board receiving less *%-for votes* than the 25^{th} (10^{th}) percentile in the respective year and industry based on Fama and French's 48 industry classification. If shareholder votes are indicative of directors' abilities to efficiently advise and monitor management, we expect the coefficients on our measures to be negative. Hence, this would suggest that unwanted directors on the board, who are in the eyes of the shareholders less capable of advising and monitoring management efficiently, are associated with a decline in subsequent stock market performance. To account for other channels influencing stock performance, we control for a variety of firm and board characteristics as well as takeover defense mechanisms. Further, we include either year and firm-fixed effects or year and industry-fixed effects based on Fama and French's 48 industry classification. Table 4.5 reports the results from these regressions.

In columns (1) and (2), we show the results from the regressions where the independent variable of interest is $\sum$*(unwanted dir., 25%$_{(y,i)}$)*. Regardless of whether we control for year and firm-fixed effects or year and industry-fixed effects, we find negative and statistically significant coefficients on our variable of interest. This finding is in line with our hypothesis suggesting a relationship between the sum of unwanted directors on a firm's board and a decline in subsequent stock market performance. The coefficients' magnitudes imply that a one-unit increase in the number of unwanted directors on the board is associated with a decline in buy-and-hold returns of 37 basis points or 36 basis points respectively.

Table 4.5: This table reports the results from Fama-MacBeth regressions of *B&h returns* on $\sum$*(unwanted dir., 25%$_{(y,i)}$)* in columns (1) and (2) and on $\sum$*(unwanted dir., 10%$_{(y,i)}$)* in columns (3) and (4). The variable $\sum$*(unwanted dir., 25%$_{(y,i)}$)* is defined as the sum of directors on a firm's board who receive less *%-for votes* ("for" votes a particular director receives divided by the the sum of all votes cast at the election) than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification). The variable $\sum$*(unwanted dir., 10%$_{(y,i)}$)* is defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level. We include control variables for firm and board characteristics as well as takeover defense mechanisms. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-fixed effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust *p*-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Dep. Variable	B&h returns$_t$			
Observations	32,590	32,590	32,590	32,590
R^2	0.1268	-0.0008	0.1266	-0.0013
R^2 **(Within)**	0.1295	0.0029	0.1293	0.0025
F-statistic	236.55	-12520	235.96	-21806
p-**value (F-stat)**	0.0000	10000	0.0000	10000
Intercept	-0.0216	-0.0270	-0.0217	-0.0277
	(0.5543)	(0.5242)	(0.5516)	(0.5138)
ln**(Firm age$_{t-1}$)**	0.0253	-0.0014	0.0251	-0.0016
	(0.1308)	(0.7142)	(0.1294)	(0.6887)
ln**(Firm size$_{t-1}$)**	-0.2330***	-0.0049	-0.2331***	-0.0050
	(0.0000)	(0.1401)	(0.0000)	(0.1338)
Stock vola.$_{t-1}$	0.1818*	-0.0269	0.1802*	-0.0299
	(0.0647)	(0.5885)	(0.0681)	(0.5555)
Tobin's Q$_{t-1}$	-0.1269***	-0.0176**	-0.1265***	-0.0174*
	(0.0000)	(0.0459)	(0.0000)	(0.0503)
Leverage$_{t-1}$	0.2838***	0.0565***	0.2829***	0.0559***
	(0.0000)	(0.0047)	(0.0000)	(0.0052)
ROE$_{t-1}$	0.0041	0.0291***	0.0041	0.0296***
	(0.7232)	(0.0000)	(0.7217)	(0.0000)
CapEx$_{t-1}$	-0.4562**	-0.1642	-0.4577**	-0.1627
	(0.0371)	(0.2671)	(0.0375)	(0.2734)
R&D$_{t-1}$	0.3300***	0.1309	0.3304***	0.1296
	(0.0000)	(0.2043)	(0.0000)	(0.2081)
ln**(Board Size)**	-0.0536	-0.0018	-0.0562	-0.0042
	(0.1198)	(0.8820)	(0.1029)	(0.7182)
Board age	0.0018***	-0.0012	0.0017***	-0.0012
	(0.0002)	(0.2362)	(0.0002)	(0.2345)
Board tenure	-0.0015**	0.0028***	-0.0016**	0.0027***
	(0.0427)	(0.0000)	(0.0384)	(0.0003)
Classified board	0.0056	0.0075	0.0062	0.0091
	(0.7074)	(0.4718)	(0.6800)	(0.3658)
Business combination provision	0.0125	0.0082	0.0115	0.0080
	(0.5086)	(0.4750)	(0.5426)	(0.4826)
Constituency provision	0.0230**	-0.0004	0.0227**	-0.0002
	(0.0274)	(0.8935)	(0.0302)	(0.9409)
Cumulative voting	0.0560	0.0138	0.0560	0.0139
	(0.1922)	(0.1123)	(0.1958)	(0.1125)
Dual class stock	0.0013	0.0021	0.0020	0.0026
	(0.9506)	(0.8469)	(0.9251)	(0.8200)
Fair price provision	3.04e-06	-0.0068	0.0008	-0.0067
	(0.9998)	(0.4002)	(0.9499)	(0.4043)
Poison pill	-0.0202**	0.0093	-0.0205**	0.0080
	(0.0269)	(0.1523)	(0.0256)	(0.2565)
Shareholder fill vacancies	0.09373	0.0051	0.0003	0.0049
	(0.9927)	(0.1575)	(0.9769)	(0.1684)
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0037***	-0.0036***		
	(0.0023)	(0.0088)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0031**	-0.0026*
			(0.0147)	(0.0783)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes

In columns (3) and (4), we use $\sum$*(unwanted dir., 10%$_{(y,i)}$)* as our variable of interest. Similar to the previous columns, the coefficients on our variable of interest are also negative and statistically significant regardless of whether we include year and firm-fixed effects or year and industry-fixed effects. However, the coefficients are slightly lower in magnitude. To put this into perspective, a one-unit increase in the sum of unwanted director using the 10^{th} percentile as a cut-off level is associated with a decrease in subsequent buy-and-hold returns of 31 basis points p.a. or 26 basis points respectively.

As regards control variables, we find that the coefficients on lagged *Tobin's Q* are negative and statistically significant throughout all specifications, while the coefficients on lagged *Leverage* are positive and statistically significant.

Next, we examine the relationship between the sum of unwanted directors on a firm's board and an alternative measure of stock market performance which is the market value of equity (MVE). To analyze this relationship, we run OLS regressions instead of Fama-MacBeth regressions. Table 4.6 presents the results from these regressions where the dependent variable is *ln(MVE)*. All independent variables and fixed-effects are similar to the previous regressions.

As expected, we also find negative and statistically coefficients on our variables of interest in all specifications. Further, the magnitudes of the coefficients are again slightly lower in the regressions where we calculate our measure based on the 10^{th} percentile as the cut-off level. In terms of control variables, we find larger firms and firms with better past performance to be positively associated with subsequent market value of equity. Moreover, firms with higher capital and R&D expenditures in the prior year as well as firms with larger boards are also positively associated with subsequent market value of equity. Firms with higher leverage and a dual class stock structure, however, are found to perform worse.

As a third measure for subsequent stock market performance, we employ *Tobin's Q*, which has been widely used in the corporate governance literature since it reflects the market's belief in whether a firm's management uses the firm's assets productively (Fracassi and Tate, 2012). Table 4.7 presents the results from OLS regressions where we use *Tobin's Q* as the dependent variable.

Table 4.6: This table reports the results from OLS regressions of *ln(MVE)* on $\sum$*(unwanted dir., 25%$_{(y,i)}$)* in columns (1) and (2) and on $\sum$*(unwanted dir., 10%$_{(y,i)}$)* in columns (3) and (4). The variable $\sum$*(unwanted dir., 25%$_{(y,i)}$)* is defined as the sum of directors on a firm's board who receive less *%-for votes* ("for" votes a particular director receives divided by the the sum of all votes cast at the election) than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification). The variable $\sum$*(unwanted dir., 10%$_{(y,i)}$)* is defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level. We include control variables for firm and board characteristics as well as takeover defense mechanisms. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-fixed effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust *p*-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Dep. Variable	$ln(MVE_t)$			
Observations	32,591	32,591	32,591	32,591
R^2	0.3121	0.8628	0.3108	0.8627
R^2 **(Within)**	0.3462	0.8474	0.3456	0.8472
F-statistic	607.70	9734.1	604.07	9723.2
p-**value (F-stat)**	0.0000	0.0000	0.0000	0.0000
Intercept	3.0150***	0.2017	3.0219***	0.2182
	(0.0000)	(0.2455)	(0.0000)	(0.2040)
ln(**Firm age**$_{t-1}$)	-0.0504*	0.0212*	-0.0498*	0.0206
	(0.0840)	(0.0993)	(0.0891)	(0.1122)
ln(**Firm size**$_{t-1}$)	0.5831***	0.9192***	0.5831***	0.9184***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
B&h returns$_{t-1}$	0.1877***	0.1899***	0.1886***	0.1907***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Stock vola.$_{t-1}$	-0.4687***	-1.0183***	-0.4736***	-1.0253***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tobin's Q$_{t-1}$	0.2194***	0.4173***	0.2201***	0.4177***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Leverage$_{t-1}$	-0.5809***	-1.0781***	-0.5835***	-1.0783***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ROE$_{t-1}$	0.0768***	0.1184***	0.0774***	0.1186***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CapEx$_{t-1}$	0.7617***	0.6690**	0.7628***	0.6717**
	(0.0000)	(0.0168)	(0.0000)	(0.0163)
R&D$_{t-1}$	0.5204***	0.8299***	0.5172***	0.8252***
	(0.0018)	(0.0000)	(0.0020)	(0.0000)
ln(**Board Size**)	0.0733**	0.2063***	0.0673**	0.2002***
	(0.0188)	(0.0008)	(0.0311)	(0.0010)
Board age	-0.0016	-0.0027*	-0.0016	-0.0027*
	(0.2923)	(0.0636)	(0.2782)	(0.0604)
Board tenure	0.0034**	0.0052**	0.0032*	0.0051**
	(0.0393)	(0.0333)	(0.0513)	(0.0371)
Classified board	0.0063	-0.0034	0.0079	0.0009
	(0.7632)	(0.8729)	(0.7081)	(0.9666)
Business combination provision	-0.0028	0.0187	-0.0032	0.0193
	(0.8698)	(0.2592)	(0.8548)	(0.2431)
Constituency provision	-0.0048	-0.0598**	-0.0068	-0.0596**
	(0.8777)	(0.0334)	(0.8295)	(0.0327)
Cumulative voting	-0.0200	-0.0015	-0.0210	-0.0017
	(0.1994)	(0.9384)	(0.1772)	(0.9305)
Dual class stock	-0.0916**	-0.0748***	-0.0895**	-0.0726***
	(0.0129)	(0.0014)	(0.0149)	(0.0015)
Fair price provision	0.0131	-0.0173	0.0151	-0.0169
	(0.6155)	(0.4770)	(0.5650)	(0.4902)
Poison pill	0.0088	0.0240	0.0076	0.0234
	(0.5796)	(0.1015)	(0.6333)	(0.1070)
Shareholder fill vacancies	0.0165	-0.0111	0.0161	-0.0115
	(0.3892)	(0.3250)	(0.4026)	(0.3045)
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0131***	-0.0113**		
	(0.0000)	(0.0128)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0122***	-0.0105*
			(0.0001)	(0.0562)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes

Table 4.7: This table reports the results from OLS regressions of *Tobin's Q* on $\sum$*(unwanted dir., 25%$_{(y,i)}$)* in columns (1) and (2) and on $\sum$*(unwanted dir., 10%$_{(y,i)}$)* in columns (3) and (4). The variable $\sum$*(unwanted dir., 25%$_{(y,i)}$)* is defined as the sum of directors on a firm's board who receive less *%-for votes* ("for" votes a particular director receives divided by the the sum of all votes cast at the election) than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification). The variable $\sum$*(unwanted dir., 10%$_{(y,i)}$)* is defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level. We include control variables for firm and board characteristics as well as takeover defense mechanisms. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-fixed effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Dep. Variable	Tobin's Q_t			
Observations	32,591	32,591	32,591	32,591
R^2	0.0888	0.1493	0.0879	0.1485
R^2 **(Within)**	0.0749	0.1435	0.0745	0.1427
F-statistic	137.09	285.37	135.60	283.49
p**-value (F-stat)**	0.0000	0.0000	0.0000	0.0000
Intercept	4.5396***	2.9299***	4.5507***	2.9628***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ln**(Firm age$_{t-1}$)**	-0.1476***	-0.0345	-0.1471***	-0.0358
	(0.0001)	(0.3038)	(0.0001)	(0.2893)
ln**(Firm size$_{t-1}$)**	-0.3506***	-0.1231***	-0.3509***	-0.1247***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
B&h returns$_{t-1}$	0.2666***	0.4664***	0.2681***	0.4683***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Stock vola.$_{t-1}$	-0.0800	-0.6637***	-0.0855*	-0.6769***
	(0.1087)	(0.0001)	(0.0864)	(0.0000)
Leverage$_{t-1}$	0.3283***	0.1104	0.3255***	0.1101
	(0.0000)	(0.4330)	(0.0001)	(0.4328)
ROE$_{t-1}$	0.0583***	0.2243***	0.0591***	0.2249***
	(0.0038)	(0.0000)	(0.0035)	(0.0000)
CapEx$_{t-1}$	0.8561***	1.9855***	0.8595***	1.9924***
	(0.0010)	(0.0091)	(0.0010)	(0.0089)
R&D$_{t-1}$	1.6317***	5.2414***	1.6301***	5.2365***
	(0.0003)	(0.0000)	(0.0003)	(0.0000)
ln**(Board Size)**	0.0312	0.2469***	0.0248	0.2361**
	(0.5202)	(0.0077)	(0.6098)	(0.0107)
Board age	-0.0016	-0.0138***	-0.0017	-0.0139***
	(0.5163)	(0.0011)	(0.5024)	(0.0011)
Board tenure	0.0107***	0.0201***	0.0106***	0.0198***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Classified board	0.0069	-0.0632	0.0086	-0.0555
	(0.8433)	(0.3296)	(0.8058)	(0.3978)
Business combination provision	0.0630**	0.0475	0.0627**	0.0487
	(0.0393)	(0.2556)	(0.0407)	(0.2479)
Constituency provision	-0.0033	0.0150	-0.0054	0.0153
	(0.9427)	(0.7306)	(0.9061)	(0.7257)
Cumulative voting	0.0246	0.0334	0.0236	0.0332
	(0.4309)	(0.4722)	(0.4505)	(0.4753)
Dual class stock	-0.1375**	-0.0719	-0.1354**	-0.0681
	(0.0250)	(0.2434)	(0.0278)	(0.2631)
Fair price provision	0.0135	-0.0927	0.0156	-0.0919
	(0.7576)	(0.1289)	(0.7210)	(0.1351)
Poison pill	-0.0270	-0.0702**	-0.0284	-0.0711**
	(0.3217)	(0.0117)	(0.2979)	(0.0123)
Shareholder fill vacancies	-0.0169	-0.0463	-0.0174	-0.0471*
	(0.5862)	(0.1035)	(0.5774)	(0.0958)
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0143***	-0.0211***		
	(0.0000)	(0.0003)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0134***	-0.0212***
			(0.0004)	(0.0078)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes

The results show a similar picture to the one found in the previous tables. Throughout all specifications, the coefficients on our variables of interest are negative and statistically significant. Thus, this provides further evidence for our hypothesis suggesting a negative association between the number of unwanted directors on a firm's board and subsequent firm performance. In terms of magnitude, a one-unit increase in the number of unwanted directors is associated with a 143 basis points decrease in *Tobin's Q*. With respect to control variables, we find firms with better performance in the prior year to be associated with higher subsequent *Tobin's Q*. Also, firms with more tenured boards are positively associated with subsequent *Tobin's Q*. In contrast, larger firms seem to perform worse.

Table 4.8: This table reports the results from OLS regressions of *ROE* on $\sum$*(unwanted dir., 25%$_{(y,i)}$)* in columns (1) and (2) and on $\sum$*(unwanted dir., 10%$_{(y,i)}$)* in columns (3) and (4). The variable $\sum$*(unwanted dir., 25%$_{(y,i)}$)* is defined as the sum of directors on a firm's board who receive less *%-for votes* ("for" votes a particular director receives divided by the the sum of all votes cast at the election) than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification). The variable $\sum$*(unwanted dir., 10%$_{(y,i)}$)* is defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level. We include control variables for firm and board characteristics as well as takeover defense mechanisms. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-fixed effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Dep. Variable	ROE$_t$			
Observations	32,586	32,586	32,586	32,586
R^2	0.0193	0.0704	0.0193	0.0706
R^2 **(Within)**	0.0209	0.0627	0.0209	0.0628
F-statistic	27647	123.12	27711	123.46
p**-value (F-stat)**	0.0000	0.0000	0.0000	0.0000
Intercept	0.2008	-0.0838	0.2004	-0.0806
	(0.1029)	(0.1179)	(0.1039)	(0.1313)
ln**(Firm age$_{t-1}$)**	0.0116	0.0161**	0.0117	0.0159**
	(0.5328)	(0.0288)	(0.5270)	(0.0305)
ln**(Firm size$_{t-1}$)**	-0.0430***	0.0103***	-0.0429***	0.0101**
	(0.0002)	(0.0088)	(0.0002)	(0.0103)
B&h returns$_{t-1}$	0.0608***	0.0741***	0.0609***	0.0740***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Stock vola.$_{t-1}$	-0.0943***	-0.3578***	-0.0953***	-0.3582***
	(0.0052)	(0.0000)	(0.0047)	(0.0000)
Tobin's Q$_{t-1}$	0.0265***	0.0367***	0.0267***	0.0367***
	(0.0002)	(0.0000)	(0.0002)	(0.0000)
Leverage$_{t-1}$	0.3503***	0.1631*	0.3501***	0.1630*
	(0.0000)	(0.0515)	(0.0000)	(0.0515)
CapEx$_{t-1}$	0.2033	0.1732	0.2031	0.1726
	(0.1506)	(0.2564)	(0.1509)	(0.2573)
R&D$_{t-1}$	-0.3732*	-1.1305***	-0.3723*	-1.1324***
	(0.0749)	(0.0000)	(0.0752)	(0.0000)
ln**(Board Size)**	-0.0110	-0.0463	-0.0118	-0.0468*
	(0.6630)	(0.1017)	(0.6383)	(0.0943)
Board age	-0.0007	0.0018*	-0.0007	0.0018*
	(0.6069)	(0.0869)	(0.6051)	(0.0874)
Board tenure	0.0003	0.0034***	0.0003	0.0034***
	(0.8022)	(0.0002)	(0.8228)	(0.0002)
Classified board	-0.0271	-0.0327**	-0.0266	-0.0325**
	(0.1292)	(0.0150)	(0.1362)	(0.0181)
Business combination provision	-0.0047	-0.0115	-0.0048	-0.0115
	(0.7070)	(0.1588)	(0.7021)	(0.1561)
Constituency provision	-0.0289*	-0.0073	-0.0297*	-0.0073
	(0.0911)	(0.3479)	(0.0828)	(0.3399)
Cumulative voting	0.0371***	0.0349***	0.0372***	0.0354***
	(0.0044)	(0.0002)	(0.0044)	(0.0002)
Dual class stock	-0.0055	0.0142	-0.0051	0.0142
	(0.8508)	(0.1686)	(0.8602)	(0.1585)
Fair price provision	-0.0271	0.0122	-0.0263	0.0123
	(0.1733)	(0.1728)	(0.1867)	(0.1692)
Poison pill	0.0127	-0.0059	0.0127	-0.0052
	(0.3292)	(0.4591)	(0.3302)	(0.5004)
Shareholder fill vacancies	-0.0142	-0.0102	-0.0141	-0.0103
	(0.2870)	(0.3130)	(0.2895)	(0.3094)
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0039**	-0.0024*		
	(0.0338)	(0.0881)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0067**	-0.0066***
			(0.0168)	(0.0019)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes

Finally, we rerun the same regressions but use the return on equity (ROE) as our dependent variable in order to analyze whether the number of unwanted directors a firm's board is also significantly associated with a decline in operating performance. Table 4.8 shows the results from these regressions.

The results suggest that the number of unwanted directors does not only have an impact on subsequent stock market performance but also on operating performance. Throughout all specifications, the coefficients on our variables of interest are negative and statistically significant. For instance, the magnitude of the smallest coefficient is -0.0024, implying that a one-unit increase in the number of unwanted directors on a firm's board is related to a decrease of 24 basis points in subsequent return on equity. Among the control variables, we find a similar pattern to the one found in Table 4.7 (*Tobin's Q*). However, the results additionally indicate a positive association between firms with cumulative voting and subsequent return on equity.

4.4.4 Dummy Regressions

To further disentangle whether the number of unwanted directors on a firm's board negatively influences subsequent firm performance, we rerun all regressions but use the dummy variables *d(unwanted dir., 25%$_{(y,i)}$, one)* and *d(unwanted dir., 25%$_{(y,i)}$, two)* as well as *d(unwanted dir., 10%$_{(y,i)}$, one)* and *d(unwanted dir., 10%$_{(y,i)}$, two)* as our variables of interest. These variables indicate whether the sum of directors per firm receiving less *%-for votes* than the 25^{th} (10^{th}) percentile in the respective year and industry is equal to one or whether it is equal to two or more. The results from these regressions are presented in Table 4.9. Although not shown for reasons of brevity, all regressions include the same control variables and fixed-effects as used in Tables 4.5 to 4.8.

As the results show, we find negative and statistically significant coefficients on our dummy variables *d(unwanted dir., 25%$_{(y,i)}$, two)* and *d(unwanted dir., 10%$_{(y,i)}$, two)* across almost all specifications. The coefficients on *d(unwanted dir., 25%$_{(y,i)}$, one)* and *d(unwanted dir., 10%$_{(y,i)}$, one)*, however, are only statistically significant for some specifications. Further, the magnitudes of the coefficients of the dummy variables indicating whether there are two or more unwanted directors on the board are significantly larger in size compared to the dummy variables indicating whether there is only one unwanted director on the firm's board. Overall, these results further support our hypothesis suggesting an association between the number of unwanted directors on a firm's board and a decline in subsequent stock and operating performance.

Table 4.9: This table reports the results from Fama-MacBeth and OLS regressions of the four stock market and operating performance measures used in the previous tables on *d(unwanted dir., 25%*$_{(y,i)}$*, one)* and *d(unwanted dir., 25%*$_{(y,i)}$*, two)* in columns (1) and (2) and on *d(unwanted dir.,* 10%$_{(y,i)}$*, one)* and *d(unwanted dir.,* 10%$_{(y,i)}$*, two)* in columns (3) and (4). The variables *d(unwanted dir., 25%*$_{(y,i)}$*, one)* and *d(unwanted dir., 25%*$_{(y,i)}$*,* $\geq$ *two)* are dummy variables indicating whether the sum of directors on a firm's board receiving less *%-for votes* than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification) is equal to one or whether it is equal to two or more. The variables *d(unwanted dir.,* 10%$_{(y,i)}$*, one)* and *d(unwanted dir.,* 10%$_{(y,i)}$*, two)* are defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level. Although not shown for reasons of brevity, all specifications include controls for firm and board characteristics as well as takeover defense mechanisms. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-fixed effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Dep. Variable	B&h returns$_t$			
Observations	32,590	32,590	32,590	32,590
R^2	0.1266	-0.0010	0.1265	-0.0014
d(unwanted dir., 25%$_{(y,i)}$, one)	-0.0092	-0.0003		
	(0.2080)	(0.9762)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	-0.0107***	-0.0102**		
	(0.0097)	(0.0175)		
d(unwanted dir., 10%$_{(y,i)}$, one)			-0.0096**	-0.0012
			(0.0370)	(0.7142)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			-0.0117**	-0.0123**
			(0.0433)	(0.0116)
Dep. Variable	$ln(MVE_t)$			
Observations	32,591	32,591	32,591	32,591
R^2	0.3110	0.8627	0.3109	0.8627
d(unwanted dir., 25%$_{(y,i)}$, one)	-0.0025	0.0167**		
	(0.7430)	(0.0474)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	-0.0368***	-0.0347**		
	(0.0000)	(0.0295)		
d(unwanted dir., 10%$_{(y,i)}$, one)			-0.0229***	-0.0064
			(0.0059)	(0.6246)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			-0.0428***	-0.0410**
			(0.0001)	(0.0243)
Dep. Variable	Tobin's Q$_t$			
Observations	32,591	32,591	32,591	32,591
R^2	0.0886	0.1498	0.0882	0.1488
d(unwanted dir., 25%$_{(y,i)}$, one)	-0.0175	-0.0373*		
	(0.1690)	(0.0956)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	-0.0588***	-0.1091***		
	(0.0000)	(0.0000)		
d(unwanted dir., 10%$_{(y,i)}$, one)			-0.0312**	-0.0513**
			(0.0234)	(0.0379)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			-0.0548***	-0.0885***
			(0.0001)	(0.0006)
Dep. Variable	ROE$_t$			
Observations	32,586	32,586	32,586	32,586
R^2	0.0193	0.0704	0.0193	0.0705
d(unwanted dir., 25%$_{(y,i)}$, one)	-0.0100	-0.0046		
	(0.1891)	(0.4598)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	-0.0162**	-0.0101*		
	(0.0392)	(0.0948)		
d(unwanted dir., 10%$_{(y,i)}$, one)			-0.0175**	-0.0097*
			(0.0217)	(0.0999)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			-0.0150	-0.0186***
			(0.1189)	(0.0081)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes
Firm controls	yes	yes	yes	yes
Board controls	yes	yes	yes	yes
Takeover defense controls	yes	yes	yes	yes

4.4.5 Stayed vs. New Unwanted Directors

In this section, we divide unwanted directors on a firm's board into two groups and rerun the same regressions as before. The first group consists of directors who have already been unwanted in the prior year and stay unwanted in the respective year, while the second group consists of directors who are only unwanted in the respective year. The rationale behind this separation is that we want to analyze whether the market already fully accounts for those unwanted directors, who stay unwanted, in the year before. If this is true, we expect the coefficients on the variables $\sum$*(unwanted dir., 25%*$_{(y,i)}$*, stayed)* and $\sum$*(unwanted dir., 10%*$_{(y,i)}$*, stayed)*, which capture the sum of unwanted directors who stay unwanted, to be rather small or even statistically insignificant in the regressions where stock market performance measures are used as the dependent variable. Yet, we expect negative and statistically significant coefficients on these variables when we use an operating performance measure as the dependent variable. This is because these directors may still have a negative impact on a firm's subsequent operating performance. On the variables $\sum$*(unwanted dir., 25%*$_{(y,i)}$*, new)* and $\sum$*(unwanted dir., 10%*$_{(y,i)}$*, new)*, however, we expect to find negative and statistically significant coefficients throughout all regressions which would provide further support for our previous findings. Table 4.10 reports the results from these regressions. Other independent variables and fixed-effects included in the regressions are similar to those used before, but are not reported due to space limits.

In columns (1) and (2), we present the results where $\sum$*(unwanted dir., 25%*$_{(y,i)}$*, stayed)* and $\sum$*(unwanted dir., 25%*$_{(y,i)}$*, new)* are our variables of interest. Regardless of whether we use stock market or operating performance measures as the dependent variable, we find negative and statistically significant coefficients on our variable $\sum$*(unwanted dir., 25%*$_{(y,i)}$*, new)*, which is in line with our expectation and our previous findings. Further, the coefficients on $\sum$*(unwanted dir., 25%*$_{(y,i)}$*, stayed)* are, as expected, statistically insignificant across almost all specifications where stock market performance measures are used as the dependent variable. The only exceptions are the regressions where *ln(MVE)* and *Tobin's Q* are used as the dependent variable and where we include firm and year-fixed effects (column 1). But statistical significance vanishes once we account for industry-fixed effects (column 2). It is, however, noteworthy that we do not find negative and statistically significant coefficients on $\sum$*(unwanted dir., 25%*$_{(y,i)}$*, stayed)* in the last regression, where we use the *ROE* as the dependent variable. Thus, we cannot conclude that directors on a firm's board who stayed unwanted still have a negative impact on subsequent operating performance.

Table 4.10: This table reports the results from OLS regressions of the four stock market and operating performance measures used in the previous tables on $\sum$*(unwanted dirs., 25%$_{y,i}$), stayed)* and $\sum$*(unwanted dirs., 25%$_{y,i}$), new)* in columns (1) and (2) and on $\sum$*(unwanted dirs., 10%$_{y,i}$), stayed)* and $\sum$*(unwanted dirs., 10%$_{y,i}$), new)* in columns (3) and (4). The variable $\sum$*(unwanted dirs., 25%$_{y,i}$), stayed)* is defined as the sum of directors on a firm's board who not only receive less *%-for votes* than the 25th percentile in the respective year and industry (based on Fama and French's 48 industry classification), but also received less *%-for votes* than the 25th percentile in the prior year and industry. The variable $\sum$*(unwanted dirs., 25%$_{y,i}$), new)*, however, is defined as the sum of directors on a firm's board who only receive less *%-for votes* than the 25th percentile in the respective year and industry. The variables $\sum$*(unwanted dirs., 10%$_{y,i}$), stayed)* and $\sum$*(unwanted dirs., 10%$_{y,i}$), new)* are defined similarly using the 10th percentile as a cut-off level. Although not shown for reasons of brevity, all specifications include controls for firm and board characteristics as well as takeover defense mechanisms. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Dep. Variable	B&h returns$_t$			
Observations	29,382	29,382	29,382	29,382
R^2	0.1308	-0.0032	0.1303	-0.0039
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0018	-0.0029		
	(0.5869)	(0.1238)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0046***	-0.0050**		
	(0.0006)	(0.0180)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			-0.0023	-0.0069
			(0.7116)	(0.2491)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0027*	-0.0018
			(0.0801)	(0.4297)
Dep. Variable	$ln(MVE_t)$			
Observations	29,383	29,383	29,383	29,383
R^2	0.3142	0.8695	0.3127	0.8693
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0167***	-0.0059		
	(0.0000)	(0.4413)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0123***	-0.0157***		
	(0.0000)	(0.0000)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			-0.0104	-0.0025
			(0.2577)	(0.8607)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0124***	-0.0124***
			(0.0001)	(0.0035)
Dep. Variable	Tobin's Q$_t$			
Observations	29,383	29,383	29,383	29,383
R^2	0.0847	0.1504	0.0835	0.1493
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0216***	-0.0108		
	(0.0000)	(0.2712)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0118***	-0.0282***		
	(0.0000)	(0.0000)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			-0.0182	-0.0023
			(0.1484)	(0.9116)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0114***	-0.0270***
			(0.0048)	(0.0006)
Dep. Variable	ROE$_t$			
Observations	29,379	29,379	29,379	29,379
R^2	0.0182	0.0686	0.0184	0.0688
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0022	0.0004		
	(0.4618)	(0.8459)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0053**	-0.0044**		
	(0.0185)	(0.0185)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			0.0085	0.0058
			(0.2334)	(0.2294)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0101***	-0.0102***
			(0.0021)	(0.0020)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes
Firm controls	yes	yes	yes	yes
Board controls	yes	yes	yes	yes
Takeover defense controls	yes	yes	yes	yes

Columns (3) and (4) show the results from the regressions where $\sum$*(unwanted dir., 10%*$_{(y,i)}$*, stayed)* and $\sum$*(unwanted dir., 10%*$_{(y,i)}$*, new)* are our variables of interest. Overall, the results support the view that directors who stayed unwanted do not have an impact on subsequent stock market and operating performance. Across all specifications, the coefficients on $\sum$*(unwanted dir., 10%*$_{(y,i)}$*, stayed)* are found to be statistically insignificant. The results concerning the impact of "newly" unwanted directors on firm performance are also in line with those found in columns (1) and (2). Except for the regressions where the *B&h returns* are used as the dependent variable, all coefficients are negative and statistically significant.

4.5 Robustness

4.5.1 Sudden Deaths

To further support our findings concerning the negative impact of unwanted directors on firm performance, we turn to an event study setting where we analyze stock price reactions to sudden deaths of corporate directors. As pointed out previously by Drobetz et al. (2018) and Nguyen and Nielsen (2010), the major advantage of analyzing sudden director deaths is that they occur randomly and are independent of firm and board characteristics. Therefore, they are recently used as identification strategy in order to address potential endogeneity problems.

We identify sudden deaths of corporate directors from companies listed on NASDAQ, NYSE or NYSE American by searching Lexis-Nexis, Factiva, Google, EDGAR, and NewsWire services (i.e. PRNewswire, BusinessWire and GlobeNewswire). We include keyword search terms such as “sudden death”, “sudden passing”, “passed away unexpectedly”, or “died suddenly” each combined with “director”, “board member”, or “chairman”. Additionally, we include terms for certain causes of sudden death such as “heart attack”, “stroke”, “crash”, or “accident”. Following previous literature (see e.g. Nguyen and Nielsen, 2010) we search in obituary notices and further newspaper articles for the exact cause of death for each of our cases and eliminate those cases where we cannot safely conclude that the death was sudden. Further, we exclude cases where confounding events might influence our analysis.

We then merge our sudden death cases with firm and director-level data obtained from our main panel. For some cases, we also hand-collect director-level data to obtain a larger sample. The final sample consists of 162 suddenly terminated directorships on 158 different firms between 2001 and 2018. However, certain controls are missing for some observations.

To conduct our event study, we start by estimating abnormal returns based on the market model. We define the day on which we find the first public announcement as $t = 0$. For cases where this day is a non-trading day, we shift the announcement date to the next trading day. Then, we estimate betas for each stock in our sample using the returns of the CRSP value-weighted index and a pre-event window of 180 trading days (from $t = -200$ to $t = -21$). Finally, we calculate abnormal returns as the difference between the stock's actual return and the stock's expected return for each trading day within an event window of 41 trading days (from $t = -20$ to $t = +20$). Following previous literature (see e.g. Betzer et al., 2020; Nguyen and Nielsen, 2010), we use the cumulative abnormal returns (CARs) winsorized at the 5$^{\text{th}}$ and the 95$^{\text{th}}$ percentile for a three-day window (i.e. from $t = -1$ to $t = 1$) and a four-day window (i.e. from $t = -1$ to $t = 2$) surrounding the event as the dependent variables in our regressions. In unreported regressions, we also use CARs based on alternative measures (e.g. Fama and French's 3-factor model) and find qualitatively similar results.

In Table 4.11, we show the results from our first set of regressions where our independent variable of interest is *%-for votes*, which is defined as the *for votes* the particular director received at the last election prior to her death divided by the sum of all votes cast. If directors' election results matter and indicate shareholders' expectation of directors' contribution to firm value, we expect the coefficient on our variable of interest to have a negative sign. Hence, this would indicate that shareholders' satisfaction with directors directly relates to directors' contribution to shareholder value.

In column (1), we report the results from a regression of the *CAR[-1,1]* surrounding the sudden deaths of outside directors on a basic set of variables related to firm, board and director characteristics, which were also used in previous studies (see e.g Drobetz et al., 2018; Nguyen and Nielsen, 2010). However, we do not include our variable of interest *%-for votes*. As the results show, we do not find any statistically significant coefficients. In column (2), we report the results from a regression including *%-for votes*. While we still do not find statistically significant coefficients on the control variables used in our baseline model, we do find a negative and statistically significant coefficient on our variable of interest *%-for votes*. In columns (3) and (4), we find similar results using the *CAR[-1,2]* as our dependent variable. We also find similar results in columns (5) and (6) where we run the same regressions but use a larger sample including the sudden deaths of inside directors.

Table 4.11: This table reports the results from OLS regressions where the dependent variables are cumulative abnormal returns (CAR) surrounding the sudden death of corporate directors. In columns (1) to (4) we report the results for a subsample consisting of outside directors only, while in columns (5) and (6) we report the results for a larger sample including inside directors. We add our variable of interest *%-for votes*, which is defined as the "for" votes a particular director received divided by the sum of all votes cast at the last election prior to her death, to our specifications in columns (2), (4), (5) and (6). Other independent variables include firm, board and director characteristics. All firm-level variables and the CARs are winsorized at the 5^{th} and 95^{th} percentiles. Further information on the variables are available in Appendix 4.B. Further, all specifications include year and industry-fixed effects based on Fama and French's 12 industry classification. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Subsample	Only outside directors				All directors	
Dep. Variable	CAR [-1,1]	CAR [-1,1]	CAR [-1,2]	CAR [-1,2]	CAR [-1,1]	CAR [-1,2]
Observations	98	98	98	98	131	131
R^2	0.2658	0.3438	0.2284	0.3075	0.2940	0.2843
Intercept	0.0552	0.1534***	0.0191	0.1221*	0.1778***	0.1808***
	(0.1633)	(0.0085)	(0.6682)	(0.0796)	(0.0001)	(0.0003)
ln(**Firm size**$_{t-1}$)	0.0015	0.0006	0.0008	-0.0001	-0.0009	0.0002
	(0.5962)	(0.8305)	(0.7730)	(0.9747)	(0.6870)	(0.9150)
ROA$_{t-1}$	0.0094	0.0241	0.0126	0.0281	-0.0122	-0.0002
	(0.7614)	(0.3677)	(0.6225)	(0.2123)	(0.5526)	(0.9923)
P/B value$_{t-1}$	-0.0025	-0.0026	-0.0017	-0.0019	-0.0046*	-0.0037
	(0.3357)	(0.2519)	(0.5485)	(0.4640)	(0.0636)	(0.1451)
Leverage$_{t-1}$	-0.0075	-0.0032	-0.0190	-0.0144	-0.0165	-0.0120
	(0.6852)	(0.8660)	(0.3400)	(0.4819)	(0.3169)	(0.5018)
Dir. age	-0.0008	-0.0008	-0.0003	-0.0003	-0.0003	0.0000
	(0.1448)	(0.1437)	(0.6712)	(0.6690)	(0.4858)	(0.9846)
Dir. tenure	0.0004	0.0004	0.0003	0.0004	0.0003	0.0002
	(0.3096)	(0.2511)	(0.3803)	(0.3072)	(0.4981)	(0.5307)
Board size	0.0000	0.0004	0.0014	0.0018	0.0017	0.0013
	(0.9994)	(0.8431)	(0.5351)	(0.4051)	(0.3766)	(0.4876)
%-for votes		-0.1015***		-0.1065**	-0.0856**	-0.1056***
		(0.0096)		(0.0316)	(0.0164)	(0.0087)
Time FE	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes

Overall, the results from our first set of regressions confirm our hypothesis that shareholders' satisfaction with directors directly relates to directors' contribution to shareholder value. To put this into perspective, a one standard deviation decrease in *%-for votes* a outside directer received is associated with an increase of 25% of a standard deviation in *CAR[-1,1]*.

To specifically test the robustness of the findings concerning the negative impact of unwanted directors on firm performance, we also run a second set of regressions where our independent variables of interest are *unwanted dir.,* $25\%_{(y,i)}$ and *unwanted dir.,* $10\%_{(y,i)}$. As before, these variables are dummy variables equalling one if the director received less *%-for votes* than the 25^{th} (10^{th}) percentile in the respective year and industry (based on Fama and French's 48-industry-classification), and zero otherwise. If these unwanted directors are associated with a negative impact on future firm performance, we expect to find positive coefficients on our variables of interest. Thus, this would indicate a more positive market reaction to the sudden deaths of unwanted directors compared to directors who received more shareholder support at the last election prior to their deaths. Table 4.12 reports the results from these regressions. In all regression, control variables are similar to the ones used before.

Table 4.12: This table reports the results from OLS regressions of the cumulative abnormal returns (CAR) surrounding the sudden death of corporate directors on *d(unwanted dir.,* $25\%_{(y,i)}$*)* in columns (1), (3), (5) and (7) and on *d(unwanted dir.,* $10\%_{(y,i)}$*)* in columns (2), (4), (6) and (8). In columns (1) to (4) the regressions are based on a subsample consisting of sudden deaths of outside directors only, while in columns (5) to (8) the regressions are based on a larger sample including inside directors. We use both the *CAR [-1,1]* and the *CAR [-1,2]* as the dependent variable and run the same specifications. The variable *d(unwanted dir.,* $25\%_{(y,i)}$*)* is a dummy variable which equals one if the director received less *%-for votes* than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification) prior to her death. The variable *unwanted dir.,* $10\%_{(y,i)}$ is defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level. Other independent variables include firm, board and director characteristics. All firm-level variables and the CARs are winsorized at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles. Further information on the variables are available in Appendix 4.B. Further, all specifications include year and industry-fixed effects based on Fama and French's 12 industry classification. Robust *p*-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Subsample	Only outside directors				All directors			
Dep. Variable	*CAR* [-1,1]	*CAR* [-1,1]	*CAR* [-1,2]	*CAR* [-1,2]	*CAR* [-1,1]	*CAR* [-1,1]	*CAR* [-1,2]	*CAR* [-1,2]
Observations	78	78	78	78	91	91	91	91
R^2	0.3997	0.4051	0.3756	0.3743	0.3438	0.3510	0.3142	0.3178
Intercept	0.0629	0.0613	0.0157	0.0138	0.0646	0.0638	0.0181	0.0171
	(0.1784)	(0.1861)	(0.7561)	(0.7830)	(0.1378)	(0.1409)	(0.6955)	(0.7113)
ln**(Firm size**$_{t-1}$**)**	0.0003	0.0005	-0.0025	-0.0023	0.0004	0.0005	-0.0016	-0.0015
	(0.9256)	(0.8864)	(0.4195)	(0.4525)	(0.8900)	(0.8505)	(0.5732)	(0.6112)
ROA$_{t-1}$	0.0145	0.0141	0.0345	0.0341	-0.0032	-0.0035	0.0135	0.0131
	(0.7116)	(0.7167)	(0.2739)	(0.2736)	(0.9167)	(0.9064)	(0.6173)	(0.6232)
MTB$_{t-1}$	-0.0034	-0.0030	-0.0025	-0.0020	-0.0043	-0.0040	-0.0032	-0.0028
	(0.2466)	(0.2891)	(0.4438)	(0.5203)	(0.1132)	(0.1313)	(0.2834)	(0.3368)
Leverage$_{t-1}$	-0.0022	-0.0003	-0.0002	0.0018	0.0054	0.0075	0.0059	0.0082
	(0.9062)	(0.9891)	(0.9928)	(0.9305)	(0.7626)	(0.6742)	(0.7608)	(0.6755)
Dir. age	-0.0011*	-0.0012*	-0.0004	-0.0005	-0.0010*	-0.0011*	-0.0004	-0.0005
	(0.0940)	(0.0787)	(0.5433)	(0.4984)	(0.0989)	(0.0804)	(0.5175)	(0.4590)
Dir. tenure	0.0005	0.0005	0.0003	0.0003	0.0004	0.0004	0.0003	0.0003
	(0.2621)	(0.2480)	(0.5007)	(0.4708)	(0.3883)	(0.3756)	(0.4813)	(0.4578)
Board size	-0.0001	-0.0000	0.0020	0.0021	-0.0002	-0.0001	0.0020	0.0021
	(0.9618)	(0.9937)	(0.4206)	(0.3954)	(0.9255)	(0.9537)	(0.4292)	(0.4062)
d**(unwanted dir.,** $25\%_{(y,i)}$**)**	0.0286**		0.0318**		0.0312***		0.0362**	
	(0.0245)		(0.0405)		(0.0069)		(0.0107)	
d**(unwanted dir.,** $10\%_{(y,i)}$**)**		0.0307**		0.0325**		0.0338***		0.0380**
		(0.0199)		(0.0474)		(0.0054)		(0.0109)
Time FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes

In columns (1) to (4), we again report the results for the subsample consisting of sudden deaths of outside directors only. Throughout all specifications, we find positive and statistically significant coefficients on our variables of interest. Further, the coefficients' magnitudes are also similar in size regardless of whether we use our measure based on the 25$^{\text{th}}$ or 10$^{\text{th}}$ percentile or whether we use an alternative window to calculate the CARs. This suggests stock market reactions to be at least 2.86% more positive for unwanted directors compared to directors with more shareholder support at the last election prior to their deaths. With respect to the control variables, we find a negative and statistically significant coefficient on *Dir. age* in columns (1) and (2). However, statistical significance vanishes when we use the *CAR[-1,2]* as the dependent variable. All other controls are found to be statistically insignificant throughout all specifications.

Finally, we also test whether these findings are robust to using a larger sample including the sudden deaths of inside directors. The results presented in columns (5) to (8) are qualitatively similar to those found in in columns (1) to (4) since we also find positive and statistically significant coefficients on our variables of interest on *unwanted dir., 25%*$_{(y,i)}$ and *unwanted dir., 10%*$_{(y,i)}$ in all regressions. Hence, this further supports our hypothesis that unwanted directors are associated with a more positive stock market reaction. Furthermore, we also find in columns (5) and (6) that *Dir. age* is associated with a more negative stock market reaction, but again statistical significance vanishes in columns (7) and (8).

Taken together the results from our first and second set of regressions, our event study approach provides evidence consistent with our previous findings. We not only find that votes are informative of shareholders' expectation of directors' contribution to firm value, but also find specifically that sudden deaths of unwanted directors are associated with a decline in firm value.

4.5.2 Trading Strategy

To additionally address concerns of endogeneity, we turn to a pair trading strategy and follow the basic line of thought proposed by Gompers et al. (2003). So if monitoring and advising by directors mattered for firm performance, but was not immediately incorporated into stock prices, and if voting was informative of a director's ability to fulfil these duties, the realized stock returns of firms having unwanted directors on the board should differ significantly from those of equivalent firms without any unwanted directors on the board.

In order to examine this relationship, we build four different pair trading strategies and compare firms with a share of more than 20%, 40%, 60% or 80% of unwanted directors on the board with equivalent firms without any unwanted directors on the board. We identify equivalent firms by selecting the indexed stock price time series for the period from one year prior to the shareholder meeting to the day before the shareholder meeting, which is co-integrated with the lowest p-value to the indexed stock price time series of the firm having the respective share of unwanted directors on the board. Additionally, we require the equivalent firm to be within the same industry (based on Fama and French's 48 industry classification). When we find a matching pair, we then buy the stock of the firm without any unwanted directors on the board and sell the stock of the firm with unwanted directors on the board for the period from two days to one year after the shareholder meeting.

Figure 4.1 visualizes the strategies' buy and hold returns for the period from 31/12/2001 to 31/12/2017. Supplementary to this, Table 4.13 reports descriptive statistics for each strategy on a monthly basis. As the results show, an initial investment of \$100 in the equally weighted pair trading strategy would have grown to \$343 by December 31, 2017 when taking firms with a share of more than 80% of unwanted directors on the board into account. When considering firms with a share of more than 60% of unwanted directors on the board, the initial investment would still have grown to \$242. This is equivalent to a mean annual return of 9.82% for the portfolio focusing on firms with a share of more than 80% of unwanted directors on the board and 5.91% for the portfolio focusing on firms with a share of more than 60% of unwanted directors on the board respectively. These results are in line with the results from our baseline regressions indicating that voting is informative of future firm performance. Additionally, the results support our finding that more than two unwanted directors on a firm's board have an adverse effect on firm performance.

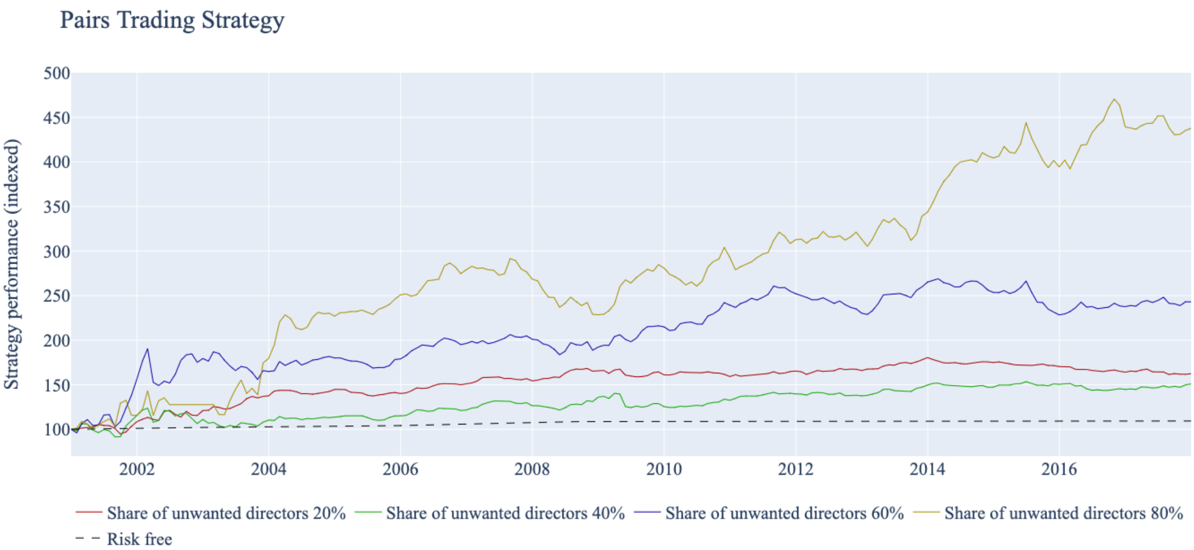

Figure 4.1: This figures visualizes the *buy & hold returns* for the four pair trading strategies based on stocks of firms having a share of more than 20%, 40%, 60% or 80% of *unwanted* directors on the board and stocks of equivalent firms without any *unwanted* directors on the board. We identify equivalent firms by selecting the indexed stock price time series for the period from one year prior to the shareholder meeting to the day before the shareholder meeting, which is co-integrated with the lowest p-value to the indexed stock price time series of the firms having the respective share of unwanted directors on the board. Each strategy is calculated for the period from 31/12/2001 to 31/12/2017.

Table 4.13: The table presents summary statistics for the four pair trading strategies illustrated in Figure 4.1. Additionally, we report the market return minus the respective risk free rate.

	Strategies (share of *unwanted* directors)				
	20%	40%	60%	80%	$Mkt-rf$
Observations	204	204	204	204	204
Mean	0.0025	0.0023	0.0050	0.0083	0.0052
Standard deviation	0.0163	0.0249	0.0351	0.0456	0.0386
10$^{\mathbf{th}}$ quantile	-0.0186	-0.0263	-0.0360	-0.0461	-0.0638
25$^{\mathbf{th}}$ quantile	-0.0053	-0.0061	-0.0109	-0.0135	-0.0102
50$^{\mathbf{th}}$ quantile	0.0014	0.0012	0.0022	0.0053	0.0115
75$^{\mathbf{th}}$ quantile	0.0083	0.0103	0.0180	0.0239	0.0286
95$^{\mathbf{th}}$ quantile	0.0261	0.0399	0.0622	0.0709	0.0520

However, the resulting returns could be driven by riskiness or "style" factors. To ensure that the results are not driven by a firm's β or other factors, or at least not by the most prominent factors (see Fama and French (1995); Carhart (1997)), we again follow Gompers et al. (2003). So we employ a three (or respectively four) factor model in Table 4.14 and a five (or respectively six) factor (Fama and French, 2015) model in Table 4.24 in the Appendix to attribute a firm's returns to these factors.

Table 4.14: This table reports the results from three(four)-factor OLS regressions of equally weighted returns derived from a pair trading strategy. We calculate the four pair trading strategies based on stocks of firms having a share of more than 20%, 40%, 60% or 80% of *unwanted* directors on the board and stocks of equivalent firms without any *unwanted* directors on the board. We identify equivalent firms by selecting the indexed stock price time series for the period from one year prior to the shareholder meeting to the day before the shareholder meeting, which is co-integrated with the lowest p-value to the indexed stock price time series of the firms having the respective share of unwanted directors on the board. Additionally, we require the equivalent company to be within the same industry (based on Fama and French's 48 industry classification). The sample period is from 31/12/2001 through 31/12/2017. Standard errors are calculated using heteroscedasticity consistent covariances (HC1). Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Strategies (share of *unwanted* directors)							
	20%		40%		60%		80%	
α	0.0021*	0.0022*	0.0025	0.0022	0.0053**	0.0052**	0.0081**	0.0083***
	(0.0654)	(0.0617)	(0.1380)	(0.2233)	(0.0255)	(0.0260)	(0.0107)	(0.0073)
$Mkt-rf$	-0.0253	-0.0308	-0.1064*	-0.0614	-0.1998***	-0.1961**	-0.1540	-0.1789
	(0.5942)	(0.4862)	(0.0760)	(0.2869)	(0.0088)	(0.0128)	(0.2400)	(0.1190)
HML	0.0225	0.0206	-0.0082	0.0075	0.0384	0.0397	0.1359	0.1273
	(0.6291)	(0.6770)	(0.9143)	(0.9235)	(0.7099)	(0.7144)	(0.3202)	(0.3694)
SMB	0.1501**	0.1509**	0.1157	0.1093	0.2216	0.2210	0.2185	0.2220
	(0.0301)	(0.0290)	(0.2289)	(0.2407)	(0.2075)	(0.2114)	(0.2003)	(0.1974)
$Momentum$	-0.0094		0.0777		0.0063		-0.0430	
	(0.7995)		(0.2117)		(0.9196)		(0.6210)	
Observations	204	204	204	204	204	204	204	204
R^2	0.033	0.034	0.023	0.037	0.043	0.043	0.024	0.025
Adj. R^2	0.019	0.014	0.009	0.018	0.029	0.024	0.009	0.005

As shown above, we report the results for each of the four different strategies. However, in conjunction with our previous analysis, we focus on columns (5) to (8) where we report the results for the two strategies based on firms with a share of more than 60% (or 80% respectively) of unwanted directors on the board and the equivalent firms without any unwanted directors on the board. We find $beta_{Mkt-rf}$ to be close to zero (also in the columns (1) to (4)), indicating the strategies to be almost market neutral. Except for columns (1) and (2), the coefficients on the "style" factors are not significant (p-value > 0.1). Importantly, the 60% strategy earns a significant monthly alpha of 53bp (52bp when controlling for momentum) with p-values < 0.05, while the 80% strategy earns a significant monthly alpha of 81bp (83bp when controlling for momentum) with p-values < 0.05 (< 0.01 respectively). For reasons of robustness, we repeat the analysis from Table 4.14 using a five (or respectively six) factor model in Table 4.24 in the Appendix, but the results remain qualitatively similar.

All in all, our pair trading strategies provide additional evidence consistent with our previous findings. Again, we find director votes to be informative of shareholders' expectation of directors' contribution to firm value. Moreover, we show that these results are not driven by market returns or the most prominent "style" factors.

4.6 Conclusion

Corporate governance matters for firm value as has been confirmed by several studies over the years. Since shareholders can and do use their votes to express dissatisfaction with particular directors these elections provide an important mechanism of corporate governance. Yet, it remained unclear whether shareholder votes contain insights about the relationship between directors' abilities to monitor and advise management efficiently and future firm performance; and thus about the effectiveness of a firm's corporate governance.

By examining a large sample of 119,126 director election events between 2001 and 2018 and 30,564 firm-year observations, we show firms with unwanted directors on the board, i.e. those with less votes for (re)election than their peers, to experience a significant decline in firm value and operating performance. The results are robust across various specifications, using different measures for stock market and operating performance as well as different measures of unwantedness. In particular, we find the number of unwanted directors on a firm's board to be the dominant driver of the decline in firm value and performance. While firms with only one unwanted director on the board do not experience a decline in subsequent firm performance, firms with two or more unwanted directors on the board do. Also, we find that directors who stayed unwanted in two consecutive years do not have an impact on stock market performance in the second year. Hence, this suggests that the market already accounts for the lack of monitoring and advising exerted by these directors in the first year.

To ensure that our results are not driven by endogeneity, we perform further robustness checks. First, we use an event study analyzing stock market reactions surrounding the sudden deaths of corporate directors. The results reveal stock markets to react more positive to the sudden deaths of unwanted directors. Thus, this provides further evidence suggesting unwanted directors to be associated with a lower contribution to shareholder value. Second, we also employ four different pair trading strategies, where we focus on firms with a certain share of unwanted directors on the board and equivalent firms without any unwanted directors on the board. In line with our previous findings, we find all strategies to be profitable, but to a lesser degree when the share of unwanted directors on the board is lower.

Overall, the results contribute significantly to the existing literature and have several implications. In extension of Cai et al. (2009) and Ertimur et al. (2018), we find that election outcomes are associated with subsequent firm performance. We also deepen the understanding of votes being informative of a director's ability to monitor and advise management efficiently (Aggarwal et al., 2019; Fos et al., 2018). Further, we contribute to the literature analyzing the value of individual directors as well as to literature examining the role of the board of directors on firm performance. Regarding implications, our results suggest that although director elections are considered routine events, their results should not be neglected by investors. As we showed convincingly, director election outcomes contain important insights about the directors' abilities to monitor and advise management efficiently and subsequent firm performance. Thus, investors should take these results into account when making their investment decisions. Moreover, our results suggest that the director nomination process might be suboptimal. Shareholders seem to anticipate whether directors contribute to shareholder value and use their votes to address this issue. Therefore, an increase in the use of proxy access might enhance the director-firm matching.

Appendix 4.A Tables

Table 4.15: This table reports the results from logit regressions (columns (1) and (3)) where the dependent variable is the dummy variable *ISS voting recommendation*, which equals one if ISS recommends voting "for" the particular director and zero otherwise. In columns (2) and (4), we report the marginal effects based on the respective logit regression. Independent variables include firm, board and director characteristics. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. In column (1), we also include firm-fixed effects, while in column (3) we include industry-fixed effects based on Fama and French's 48 industry classification. Standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Dep. Variable	ISS voting recommendation			
	Logit	$\partial y/\partial x$	Logit	$\partial y/\partial x$
Observations	191,009		191,009	
Pseudo-R^2	0.0326		0.0718	
Intercept	2.3329***		2.4473***	
	(0.0000)		(0.0000)	
ln**(Firm age$_{t-1}$)**	0.7669***	0.0638***	0.4395***	0.0354***
	(0.0010)	(0.0020)	(0.0000)	(0.0000)
ln**(Firm size$_{t-1}$)**	0.0946	0.0079	0.0921***	0.0074***
	(0.2492)	(0.2590)	(0.0007)	(0.0010)
B&h returns$_{t-1}$	0.1709***	0.0142***	0.1853***	0.0149***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Stock vola.$_{t-1}$	-0.5072***	-0.0422***	-0.6853***	-0.0552***
	(0.0004)	(0.0010)	(0.0000)	(0.0000)
Tobin's Q$_{t-1}$	0.0691***	0.0057***	0.0284	0.0023
	(0.0051)	(0.0050)	(0.2708)	(0.2660)
Leverage$_{t-1}$	0.0715	0.0059	-0.0955	-0.0077
	(0.7447)	(0.7460)	(0.5637)	(0.5650)
ROE$_{t-1}$	0.0529	0.0044	0.1052***	0.0085***
	(0.1552)	(0.1550)	(0.0093)	(0.0080)
CapEx$_{t-1}$	-0.8639	-0.0718	1.2977	0.1046
	(0.2069)	(0.2130)	(0.1313)	(0.1400)
R&D$_{t-1}$	-2.4650***	-0.2050***	0.6702	0.054
	(0.0000)	(0.0000)	(0.1236)	(0.1330)
ln**(Board size)**	-0.2359	-0.0196	0.1018	0.0082
	(0.2561)	(0.2650)	(0.6273)	(0.6240)
Board age	0.0161**	0.0013**	0.0147***	0.0012***
	(0.0292)	(0.0320)	(0.0068)	(0.0080)
Board tenure	-0.0248**	-0.0021**	-0.0337***	-0.0027***
	(0.0113)	(0.0140)	(0.0000)	(0.0000)
Active ownership	-0.2713	-0.0226	-0.9429***	-0.0760***
	(0.2571)	(0.2600)	(0.0000)	(0.0000)
Outside director	0.1849***	0.0154***	0.3134***	0.0253***
	(0.0003)	(0.0000)	(0.0000)	(0.0000)
Attendance	-2.2235***	-0.1849***	-2.3118***	-0.1863***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Problem dir.	0.0243	0.002	-0.0036	-0.0003
	(0.6660)	(0.6660)	(0.9629)	(0.9630)
Dir. ownership	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Dir. tenure	-0.0282***	-0.0023***	-0.0312***	-0.0025***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Dir. age	0.0111***	0.0009***	0.0098***	0.0008***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Dir. gender	-0.0976***	-0.0081***	-0.1943***	-0.0157***
	(0.0033)	(0.0040)	(0.0000)	(0.0000)
Busy dir.	-0.1460***	-0.0121***	-0.1069***	-0.0086***
	(0.0000)	(0.0000)	(0.0030)	(0.0040)
Any CEO	0.0142	0.0012	0.1364***	0.011
	(0.6943)	(0.6940)	(0.0055)	(0.0100)
Founder	-0.1702**	-0.0142**	-0.0013	-0.0001
	(0.0391)	(0.0370)	(0.9889)	(0.9890)
Company CEO	0.0811	0.0067	0.2572***	0.0207***
	(0.2116)	(0.2090)	(0.0003)	(0.0010)
Military	0.0348	0.0029	0.0708	0.0057
	(0.8310)	(0.8310)	(0.6624)	(0.6620)
Professor	0.1266	0.0105	0.0575	0.0046
	(0.2887)	(0.2890)	(0.7227)	(0.7230)
Ph.D.	-0.0488	-0.0041	-0.0932	-0.0075
	(0.3219)	(0.3230)	(0.1647)	(0.1730)
C. lead	0.0507	0.0042	0.1921***	0.0155***
	(0.1131)	(0.1140)	(0.0000)	(0.0000)
C. non chair	-0.0172	-0.0014	0.0244	0.002
	(0.5838)	(0.5810)	(0.5843)	(0.5860)
Year FE	yes		yes	
Firm FE	yes		no	
Industry FE	no		yes	
Director FE	no		no	

Table 4.16: This table reports the results from OLS regressions where the dependent variable is *excess votes* in columns (1) to (3) and *excess votes excl. lowest* in columns (4) to (6). The variable *excess votes* is calculated as a director's *%-for votes* ("for" votes a particular director receives divided by the the sum of all votes cast at the election) minus the average *%-for votes* over all directors at the company's election. The variable *excess votes excl. lowest*, however, is calculated as a director's *%-for votes* minus the average *%-for votes* over all directors at the company's election excluding the director with the lowest *%-for votes*. Independent variables include firm, board and director characteristics. Following Cai et al. (2009), we also include the residuals from a logistic regression, where the ISS recommendation is explained by various firm, board and director characteristics, as a further control variable named *ISS estimation*. All variables are defined in Appendix 4.B. All specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3), industry-fixed effects based on Fama and French's 48 industry classification in columns (2) and (4), and firm and director-fixed effects in columns (3) and (6). Across all columns, standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Variable	excess votes			excess votes excl. lowest		
Observations	191,126	191,126	191,126	191,126	191,126	191,126
R^2	0.2621	0.2098	0.2110	0.2911	0.2455	0.2482
R^2 **(Within)**	0.2594	0.2081	0.2117	0.2896	0.2440	0.2487
F-statistic	2211.2	1690.9	2221.9	2556.4	2071.8	2742.1
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Intercept	-0.0024	0.0007	0.0000	-0.0161	-0.0271***	-0.0000
	(0.8636)	(0.8077)	(0.6475)	(0.1575)	(0.0000)	(0.8344)
ln(**Firm age**$_{t-1}$)	0.0009	0.0005	-0.0009*	0.0012	0.0016***	0.0000
	(0.7060)	(0.1191)	(0.0516)	(0.5384)	(0.0000)	(0.9438)
ln(**Firm size**$_{t-1}$)	0.0004	0.0000	0.0000	0.0001	0.0005***	0.0005**
	(0.4876)	(0.5536)	(0.7870)	(0.7781)	(0.0034)	(0.0337)
B&h returns$_{t-1}$	0.0000	-0.0000	-0.0000	0.0005	-7.7e-05	0.0002
	(0.7691)	(0.7812)	(0.9269)	(0.1433)	(0.8278)	(0.4836)
Stock vola.$_{t-1}$	-0.0007	-0.0000	0.0019	0.0000	0.0004	0.0019*
	(0.5684)	(0.9528)	(0.1299)	(0.9503)	(0.7310)	(0.0983)
Tobin's Q$_{t-1}$	-0.0000	-0.0000	0.0000	-0.0000	0.0003	0.0004*
	(0.9913)	(0.9384)	(0.7014)	(0.9238)	(0.1933)	(0.0527)
Leverage$_{t-1}$	0.0006	-0.0003	-0.0008	0.0009	0.0011	0.0001
	(0.7372)	(0.7957)	(0.5329)	(0.6182)	(0.3636)	(0.9158)
ROE$_{t-1}$	-0.0000	-0.0000	-0.0000	-0.0000	0.0001	-0.0000
	(0.9427)	(0.8050)	(0.7123)	(0.9420)	(0.6914)	(0.8248)
CapEx$_{t-1}$	-0.0015	-0.0019	0.0019	0.0033	0.0024	0.0048
	(0.7780)	(0.7468)	(0.6533)	(0.5750)	(0.7033)	(0.2565)
R&D$_{t-1}$	0.0044	0.0024	-0.0013	0.0030	0.0005	-0.0028
	(0.5854)	(0.4685)	(0.7224)	(0.7114)	(0.8741)	(0.4902)
ln(**Board size**)	-0.0006	0.0012	0.0021**	0.0020	0.0063***	0.0050***
	(0.5969)	(0.4072)	(0.0276)	(0.1283)	(0.0001)	(0.0000)
Board age	0.0000	-0.0000	0.0000	0.0000	-0.0000	0.0000
	(0.2179)	(0.9746)	(0.5102)	(0.3209)	(0.8376)	(0.7527)
Board tenure	0.0004***	0.0007***	0.0007***	0.0004***	0.0006***	0.0006***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Active ownership	0.0004	0.0000	0.0028**	0.0009	0.0002	0.0030**
	(0.8531)	(0.9294)	(0.0197)	(0.7230)	(0.8377)	(0.0146)
Outside director	-0.0020***	-0.0021**	-0.0042***	-0.0024***	-0.0027**	-0.0047***
	(0.0003)	(0.0243)	(0.0000)	(0.0000)	(0.0126)	(0.0000)
Attendance	-0.0869***	-0.0820***	-0.0877***	-0.0979***	-0.0950***	-0.1008***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Problem dir.	-0.0021**	-0.0019**	-0.0017	-0.0024***	-0.0021***	-0.0016
	(0.0164)	(0.0192)	(0.2335)	(0.0075)	(0.0089)	(0.2973)
Dir. ownership	-0.0000***	-0.0000***	0.0000	-0.0000**	-0.0000*	2.894e-08**
	(0.0083)	(0.0307)	(0.1126)	(0.0233)	(0.0996)	(0.0454)
Dir. tenure	-0.0009***	-0.0009***	-0.0007***	-0.0009***	-0.0009***	-0.0007***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Dir. age	0.0000***	0.0000***	-0.0004***	0.0000***	0.0000***	-0.0003***
	(0.0001)	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Dir. gender	-0.0027***	-0.0024***		-0.0031***	-0.0031***	
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	
Busy dir.	-0.0074***	-0.0067***	-0.0031***	-0.0079***	-0.0072***	-0.0035***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Any CEO	0.0020***	0.0020***	-0.0003	0.0019***	0.0017**	-0.0003
	(0.0001)	(0.0025)	(0.6732)	(0.0001)	(0.0156)	(0.7282)
Founder	0.0008	0.0005		-0.0001	-0.0013	
	(0.5777)	(0.7687)		(0.9380)	(0.4773)	
Company CEO	0.0044***	0.0045***	0.0005	0.0040***	0.0041***	-0.0000
	(0.0000)	(0.0000)	(0.5096)	(0.0000)	(0.0000)	(0.9882)
Military	0.0040***	0.0038***		0.0043***	0.0046***	
	(0.0055)	(0.0085)		(0.0033)	(0.0009)	
Professor	0.0024*	0.0023		0.0023	0.0027	
	(0.0925)	(0.1536)		(0.1227)	(0.1306)	
Ph.D.	-0.0007	-0.0008		-0.0006	-0.0009	
	(0.3595)	(0.2664)		(0.3858)	(0.1969)	
C. lead	-0.0031***	-0.0029***		-0.0031***	-0.0029***	
	(0.0000)	(0.0000)		(0.0000)	(0.0000)	
C. Non chair	-0.0011***	-0.0012***		-0.0013***	-0.0013***	
	(0.0002)	(0.0000)		(0.0000)	(0.0000)	
ISS estimation	0.0891***	0.0689***	0.0792***	0.0980***	0.0788***	0.0901***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Year FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	no	no	yes	no	no
Industry FE	no	yes	yes	no	yes	yes
Director FE	no	no	yes	no	no	yes

Table 4.17: This table reports the results from OLS regressions where the dependent variable is *%-for votes*, which is calculated as the "for" votes a particular director receives divided by the the sum of all votes cast at the election. In columns (1) and (2) we interact a variety of control variables for firm, board and director characteristics with the dummy variable *unwanted dir., 25%*$_{(y,i)}$, while in columns (3) and (4) we interact these variables with the dummy variable *unwanted dir., 10%*$_{(y,i)}$. The dummy variable *unwanted dir., 25%*$_{(y,i)}$ equals one if the particular director receives less *%-for votes* than the 25th percentile in the respective year and industry (based on Fama and French's 48 industry classification), and zero otherwise. The dummy variable *unwanted dir., 10%*$_{(y,i)}$ is defined similarly using the 10th percentile as a cut-off level. For reasons of brevity, we do not report the results for the uninteracted variables. All variables are defined in Appendix 4.B. Further, all regressions include year-fixed effects. In columns (1) and (3) we also include firm-fixed effects, while in columns (2) and (4) we include industry-fixed effects based on Fama and French's 48 industry classification. Standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Dep. Variable	*%-for votes*			
	M = 25% year, industry		M = 10% year, industry	
Observations	191,126	191,126	191,126	191,126
R^2	0.6264	0.6220	0.6810	0.6711
R^2 **(Within)**	0.6249	0.6225	0.6803	0.6716
F-statistic	5133.1	6538.8	6534.7	8107.1
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000
ln**(Firm age**$_{t-1}$**):M**	-0.0080***	-0.0064***	-0.0092***	-0.0067***
	(0.0000)	(0.0000)	(0.0003)	(0.0056)
ln**(Firm size**$_{t-1}$**):M**	0.0038***	0.0050***	0.0046***	0.0067***
	(0.0000)	(0.0000)	(0.0008)	(0.0000)
B&h returns$_{t-1}$**:M**	0.0055***	0.0061***	0.0074**	0.0093***
	(0.0025)	(0.0005)	(0.0180)	(0.0025)
Stock vola.$_{t-1}$**:M**	-0.0279***	-0.0289***	-0.0436***	-0.0452***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Tobin's Q$_{t-1}$**:M**	0.0013	0.0026**	-0.0001	0.0012
	(0.2389)	(0.0118)	(0.9468)	(0.5062)
Leverage$_{t-1}$**:M**	0.0281***	0.0288***	0.0335***	0.0321***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ROE$_{t-1}$**:M**	-0.0013	-0.0019	-0.0051	-0.0049
	(0.5986)	(0.4622)	(0.1897)	(0.2417)
CapEx$_{t-1}$**:M**	0.0497**	0.0433**	0.0590*	0.0608*
	(0.0119)	(0.0252)	(0.0589)	(0.0618)
R&D$_{t-1}$**:M**	0.0108	0.0019	0.0046	0.0005
	(0.5397)	(0.9153)	(0.8730)	(0.9866)
ln**(Board size):M**	0.0057	0.0029	0.0053	0.0022
	(0.2655)	(0.5538)	(0.5210)	(0.7876)
Board age:M	-0.0006**	-0.0005**	-0.0007*	-0.0007*
	(0.0161)	(0.0395)	(0.0657)	(0.0610)
Board tenure:M	0.0012***	0.0011***	0.0015***	0.0015***
	(0.0003)	(0.0027)	(0.0058)	(0.0081)
Active owners.:M	0.0256***	0.0198***	0.0290***	0.0245***
	(0.0000)	(0.0007)	(0.0012)	(0.0061)
Outside dir. :M	-0.0128***	-0.0142***	-0.0157***	-0.0146***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Attendance:M	-0.0872***	-0.0768***	-0.0594***	-0.0590***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Problem dir.:M	-0.0031	-0.0030	0.0032	0.0014
	(0.1992)	(0.2451)	(0.4800)	(0.7550)
Dir. owners.:M	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0001)	(0.0000)	(0.0044)	(0.0038)
Dir. tenure:M	-0.0000	0.0003***	0.0004***	0.0005***
	(0.5226)	(0.0038)	(0.0010)	(0.0013)
Dir. age:M	0.0000	-0.0000	0.0000	-0.0002*
	(0.6605)	(0.1423)	(0.9869)	(0.0510)
Dir. gender:M	-0.0021		-0.0010	
	(0.1610)		(0.7132)	
Busy dir.:M	-0.0018	-0.0007	0.0020	0.0014
	(0.2104)	(0.6147)	(0.4562)	(0.5875)
Any CEO:M	0.0043**	0.0016	0.0034	-0.0019
	(0.0110)	(0.3490)	(0.2509)	(0.5524)
Founder:M	-0.0083**		-0.0121**	
	(0.0325)		(0.0336)	
Company CEO:M	0.0086***	0.0067**	0.0046	0.0042
	(0.0041)	(0.0281)	(0.4794)	(0.5505)
Military:M	0.0168***		0.0187*	
	(0.0010)		(0.0613)	
Professor:M	0.0027		-0.0078	
	(0.6305)		(0.4846)	
Ph.D.:M	0.0002		-0.0040	
	(0.9523)		(0.3837)	
C. lead:M	-0.0059***		-0.0071***	
	(0.0002)		(0.0041)	
C. Non chair:M	-0.0004		0.0018	
	(0.7529)		(0.3966)	
ISS estimation:M	0.1157***	0.1107***	0.0539***	0.0515***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry FE	no	no	no	no
Director FE	no	yes	no	yes
Controls	yes	yes	yes	yes

Table 4.18: This table reports the results from OLS regressions of the four stock market and operating performance measures used in the previous tables on $\sum$*(unwanted dirs., 25%$_{(y,i)}$)* in columns (1) and (2) and on $\sum$*(unwanted dirs., 10%$_{(y,i)}$)* in columns (3) and (4) for a subsample of firms with at least one outside director on the board. The variable $\sum$*(unwanted dirs., 25%$_{(y,i)}$)* is defined as the sum of outside directors on a firm's board who receive less *%-for votes* than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification). The variable $\sum$*(unwanted dirs., 10%$_{(y,i)}$)* is defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level. Although not shown for reasons of brevity, all specifications include controls for firm and board characteristics as well as takeover defense mechanisms. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Subsample	Outside directors only			
Dep. Variable	B&h returns$_t$			
Observations	32,496	32,496	32,496	32,496
R^2	0.1270	-0.0009	0.1267	-0.0016
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0044***	-0.0040***		
	(0.0001)	(0.0091)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0033**	-0.0026*
			(0.0247)	(0.0956)
Dep. Variable	$ln(MVE_t)$			
Observations	32,497	32,497	32,497	32,497
R^2	0.3129	0.8629	0.3115	0.8628
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0159***	-0.0119**		
	(0.0000)	(0.0184)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0146***	-0.0106*
			(0.0001)	(0.0928)
	Tobin's Q$_t$			
Observations	32,497	32,497	32,497	32,497
R^2	0.0891	0.1502	0.0880	0.1493
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0176***	-0.0252***		
	(0.0000)	(0.0001)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0153***	-0.0254***
			(0.0005)	(0.0041)
Dep. Variable	ROE$_t$			
Observations	32,492	32,492	32,492	32,492
R^2	0.0193	0.0705	0.0193	0.0706
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0050**	-0.0032*		
	(0.0175)	(0.0504)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0081***	-0.0078***
			(0.0095)	(0.0022)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes
Firm controls	yes	yes	yes	yes
Board controls	yes	yes	yes	yes
Takeover defense controls	yes	yes	yes	yes

Table 4.19: This table reports the results from OLS regressions of the four stock market and operating performance measures used in the previous tables on $\sum$*(unwanted dirs., 25%$_{(y,i)}$)* in columns (1) and (2) and on $\sum$*(unwanted dirs., 10%$_{(y,i)}$)* in columns (3) and (4) for a subsample of firms with at least one "unwanted" outside director on the board. The variable $\sum$*(unwanted dirs., 25%$_{(y,i)}$)* is defined as the sum of outside directors on a firm's board who receive less *%-for votes* than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification). The variable $\sum$*(unwanted dirs., 10%$_{(y,i)}$)* is defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level. Although not shown for reasons of brevity, all specifications include controls for firm and board characteristics as well as takeover defense mechanisms. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Subsample	Firms with unwanted outside directors only			
Dep. Variable	B&h returns$_t$			
Observations	16,773	16,773	8,335	8,335
R^2	0.1248	0.0001	0.1222	-0.0034
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0032**	-0.0053***		
	(0.0461)	(0.0000)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0023	-0.0004
			(0.1389)	(0.8576)
Dep. Variable	$ln(MVE_t)$			
Observations	16,773	16,773	8,335	8,335
R^2	0.3112	0.8707	0.3000	0.8653
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0194***	-0.0167***		
	(0.0000)	(0.0013)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0140**	-0.0068
			(0.0357)	(0.2919)
Dep. Variable	Tobin's Q$_t$			
Observations	16,773	16,773	8,335	8,335
R^2	0.0825	0.1441	0.0873	0.1496
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0144***	-0.0213***		
	(0.0000)	(0.0024)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0008	-0.0091
			(0.9217)	(0.2969)
Dep. Variable	ROE$_t$			
Observations	16,772	16,772	8,334	8,334
R^2	0.0199	0.0711	0.0184	0.0805
$\sum$***(unwanted dir., 25%$_{(y,i)}$)***	-0.0020	-0.0025		
	(0.4723)	(0.2524)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$)***			-0.0069	-0.0086**
			(0.2470)	(0.0211)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes
Firm controls	yes	yes	yes	yes
Board controls	yes	yes	yes	yes
Takeover defense controls	yes	yes	yes	yes

Table 4.20: This table reports the results from OLS regressions of the four stock market and operating performance measures used in the previous tables on *d(unwanted dir., 25%$_{(y,i)}$, one)* and *d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)* in columns (1) and (2) and on *d(unwanted dir., 10%$_{(y,i)}$, one)* and *d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)* in columns (3) and (4). The regressions are based on a subsample of firms with at least one outside director on the board. The variables *d(unwanted dir., 25%$_{(y,i)}$, one)* and *d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)* are dummy variables indicating whether the sum of outside directors on a firm's board receiving less *%-for votes* than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification) is equal to one or whether it is equal to two or more. The variables *d(unwanted dir., 10%$_{(y,i)}$, one)* and *d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)* are defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level. Although not shown for reasons of brevity, all specifications include controls for firm and board characteristics as well as takeover defense mechanisms. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-fixed effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Subsample	Outside directors only			
Dep. Variable	B&h returns$_t$			
Observations	32,496	32,496	32,496	32,496
R^2	0.1268	-0.0013	0.1266	-0.0016
d(unwanted dir., 25%$_{(y,i)}$, one)	-0.0086*	-0.0038		
	(0.0734)	(0.5507)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	-0.0105**	-0.0094*		
	(0.0203)	(0.0823)		
d(unwanted dir., 10%$_{(y,i)}$, one)			-0.0075	-0.0009
			(0.1504)	(0.8081)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			-0.0121**	-0.0117**
			(0.0172)	(0.0291)
Dep. Variable	$ln(MVE_t)$			
Observations	32,497	32,497	32,497	32,497
R^2	0.3117	0.8628	0.3116	0.8628
d(unwanted dir., 25%$_{(y,i)}$, one)	-0.0049	0.0073		
	(0.5172)	(0.4008)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	-0.0406***	-0.0301*		
	(0.0000)	(0.0601)		
d(unwanted dir., 10%$_{(y,i)}$, one)			-0.0232***	-0.0052
			(0.0054)	(0.6471)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			-0.0480***	-0.0382**
			(0.0000)	(0.0476)
Dep. Variable	Tobin's Q$_t$			
Observations	32,497	32,497	32,497	32,497
R^2	0.0888	0.1504	0.0882	0.1495
d(unwanted dir., 25%$_{(y,i)}$, one)	-0.0214*	-0.0453*		
	(0.0865)	(0.0638)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	-0.0637***	-0.1088***		
	(0.0000)	(0.0000)		
d(unwanted dir., 10%$_{(y,i)}$, one)			-0.0249*	-0.0329
			(0.0768)	(0.1542)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			-0.0564***	-0.0948***
			(0.0001)	(0.0016)
Dep. Variable	ROE$_t$			
Observations	32,492	32,492	32,492	32,492
R^2	0.0193	0.0704	0.0193	0.0706
d(unwanted dir., 25%$_{(y,i)}$, one)	-0.0086	-0.0053		
	(0.2746)	(0.4216)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	-0.0180**	-0.0117*		
	(0.0237)	(0.0582)		
d(unwanted dir., 10%$_{(y,i)}$, one)			-0.0142*	-0.0083
			(0.0627)	(0.1814)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			-0.0190*	-0.0219***
			(0.0630)	(0.0067)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes
Firm controls	yes	yes	yes	yes
Board controls	yes	yes	yes	yes
Takeover defense controls	yes	yes	yes	yes

Table 4.21: This table reports the results from OLS regressions of the four stock market and operating performance measures used in the previous tables on *d(unwanted dir., 25%$_{(y,i)}$, one)* and *d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)* in columns (1) and (2) and on *d(unwanted dir., 10%$_{(y,i)}$, one)* and *d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)* in columns (3) and (4). The regressions are based on a subsample of firms with at least one "unwanted" outside director on the board. The variables *d(unwanted dir., 25%$_{(y,i)}$, one)* and *d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)* are dummy variables indicating whether the sum of outside directors on a firm's board receiving less *%-for votes* than the 25$^{\text{th}}$ percentile in the respective year and industry (based on Fama and French's 48 industry classification) is equal to one or whether it is equal to two or more. The variables *d(unwanted dir., 10%$_{(y,i)}$, one)* and *d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)* are defined similarly using the 10$^{\text{th}}$ percentile as a cut-off level. Although not shown for reasons of brevity, all specifications include controls for firm and board characteristics as well as takeover defense mechanisms. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-fixed effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust *p*-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Subsample	Firms with unwanted outside directors only			
Dep. Variable	B&h returns$_t$			
Observations	16,798	16,798	8,350	8,350
R^2	0.1247	-0.0008	0.1237	-0.0026
d(unwanted dir., 25%$_{(y,i)}$, one)	0.0030	0.0010		
	(0.8732)	(0.9446)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	0.0044	-0.0052		
	(0.8386)	(0.7520)		
d(unwanted dir., 10%$_{(y,i)}$, one)			-0.0198**	-0.0042
			(0.0256)	(0.7544)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			-0.0285***	-0.0141
			(0.0040)	(0.3355)
Dep. Variable	$ln(MVE_t)$			
Observations	16,798	16,798	8,350	8,350
R^2	0.3078	0.8702	0.2982	0.8651
d(unwanted dir., 25%$_{(y,i)}$, one)	-0.0079	0.0185		
	(0.6768)	(0.3979)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	-0.0462**	-0.0202		
	(0.0153)	(0.2812)		
d(unwanted dir., 10%$_{(y,i)}$, one)			-0.0243	0.0392
			(0.4549)	(0.2668)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			-0.0623*	0.0064
			(0.0581)	(0.8786)
Dep. Variable	Tobin's Q$_t$			
Observations	16,798	16,798	8,350	8,350
R^2	0.0824	0.1439	0.0885	0.1512
d(unwanted dir., 25%$_{(y,i)}$, one)	-0.0206	-0.0159		
	(0.5011)	(0.7224)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	-0.0574*	-0.0907**		
	(0.0547)	(0.0446)		
d(unwanted dir., 10%$_{(y,i)}$, one)			0.0826	0.0997**
			(0.1139)	(0.0102)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			0.0526	0.0341
			(0.2944)	(0.4675)
Dep. Variable	ROE$_t$			
Observations	16,797	16,797	8,349	8,349
R^2	0.0200	0.0710	0.0185	0.0810
d(unwanted dir., 25%$_{(y,i)}$, one)	-0.0030	-0.0085		
	(0.8773)	(0.6031)		
d(unwanted dir., 25%$_{(y,i)}$, $\geq$ two)	-0.0069	-0.0144		
	(0.7276)	(0.3633)		
d(unwanted dir., 10%$_{(y,i)}$, one)			0.0003	0.0027
			(0.9926)	(0.8916)
d(unwanted dir., 10%$_{(y,i)}$, $\geq$ two)			-0.0068	-0.0133
			(0.8309)	(0.4807)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes
Firm controls	yes	yes	yes	yes
Board controls	yes	yes	yes	yes
Takeover defense controls	yes	yes	yes	yes

Table 4.22: This table reports the results from OLS regressions of the four stock market and operating performance measures used in the previous tables on $\sum$*(unwanted dirs., 25%$_{(y,i)}$), stayed)* and $\sum$*(unwanted dirs., 25%$_{(y,i)}$), new)* in columns (1) and (2) and on $\sum$*(unwanted dirs., 10%$_{(y,i)}$), stayed)* and $\sum$*(unwanted dirs., 10%$_{(y,i)}$), new)* in columns (3) and (4). The regressions are based on a subsample of firms with at least one outside director on the board. The variable $\sum$*(unwanted dirs., 25%$_{(y,i)}$), stayed)* is defined as the sum of outside directors on a firm's board who not only receive less *%-for votes* than the 25th percentile in the respective year and industry (based on Fama and French's 48 industry classification), but also received less *%-for votes* than the 25th percentile in the prior year and industry. The variable $\sum$*(unwanted dirs., 25%$_{(y,i)}$), new)*, however, is defined as the sum of outside directors on a firm's who only receive less *%-for votes* than the 25th percentile in the respective year and industry. The variables $\sum$*(unwanted dirs., 10%$_{(y,i)}$), stayed)* and $\sum$*(unwanted dirs., 10%$_{(y,i)}$), new)* are defined similarly using the 10th percentile as a cut-off level. Although not shown for reasons of brevity, all specifications include controls for firm and board characteristics as well as takeover defense mechanisms. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Subsample	Outside directors only			
Dep. Variable	B&h returns$_t$			
Observations	29,283	29,283	29,283	29,283
R^2	0.1308	-0.0027	0.1303	-0.0035
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0026	-0.0034		
	(0.5708)	(0.1558)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0052***	-0.0056**		
	(0.0004)	(0.0198)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			-0.0084	-0.0137
			(0.3809)	(0.1115)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0022	-0.0007
			(0.2016)	(0.7211)
Dep. Variable	$ln(MVE_t)$			
Observations	29,284	29,284	29,284	29,284
R^2	0.3142	0.8693	0.3125	0.8692
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0204***	-0.0032		
	(0.0000)	(0.7360)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0146***	-0.0174***		
	(0.0000)	(0.0000)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			-0.0175	-0.0016
			(0.1489)	(0.9358)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0142***	-0.0123***
			(0.0001)	(0.0054)
Dep. Variable	Tobin's Q$_t$			
Observations	29,284	29,284	29,284	29,284
R^2	0.0851	0.1505	0.0837	0.1502
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0286***	-0.0161		
	(0.0000)	(0.1126)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0138***	-0.0311***		
	(0.0000)	(0.0000)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			-0.0329**	-0.0095
			(0.0225)	(0.7166)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0121***	-0.0298***
			(0.0085)	(0.0004)
Dep. Variable	ROE$_t$			
Observations	29,280	29,280	29,280	29,280
R^2	0.0182	0.0689	0.0184	0.0691
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0022	0.0006		
	(0.5129)	(0.8345)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0066**	-0.0055***		
	(0.0107)	(0.0087)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			0.0129	0.0058
			(0.1757)	(0.3575)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0117***	-0.0111***
			(0.0010)	(0.0020)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes
Firm controls	yes	yes	yes	yes
Board controls	yes	yes	yes	yes
Takeover defense controls	yes	yes	yes	yes

Table 4.23: This table reports the results from OLS regressions of the four stock market and operating performance measures used in the previous tables on $\sum$*(unwanted dirs., 25%$_{(y,i)}$), stayed)* and $\sum$*(unwanted dirs., 25%$_{(y,i)}$), new)* in columns (1) and (2) and on $\sum$*(unwanted dirs., 10%$_{(y,i)}$), stayed)* and $\sum$*(unwanted dirs., 10%$_{(y,i)}$), new)* in columns (3) and (4). The regressions are based on a subsample of firms with at least one "unwanted" outside director on the board. The variable $\sum$*(unwanted dirs., 25%$_{(y,i)}$), stayed)* is defined as the sum of outside directors on a firm's board who not only receive less *%-for votes* than the 25th percentile in the respective year and industry (based on Fama and French's 48 industry classification), but also received less *%-for votes* than the 25th percentile in the prior year and industry. The variable $\sum$*(unwanted dirs., 25%$_{(y,i)}$), new)*, however, is defined as the sum of outside directors on a firm's board who only receive less *%-for votes* than the 25th percentile in the respective year and industry. The variables $\sum$*(unwanted dirs., 10%$_{(y,i)}$), stayed)* and $\sum$*(unwanted dirs., 10%$_{(y,i)}$), new)* are defined similarly using the 10th percentile as a cut-off level. Although not shown for reasons of brevity, all specifications include controls for firm and board characteristics as well as takeover defense mechanisms. All variables are defined in Appendix 4.B. Further, all specifications include year-fixed effects. We also include firm-fixed effects in columns (1) and (3) and industry-effects based on Fama and French's 48 industry classification in columns (2) and (4). Standard errors are clustered by firm or by industry, respectively. Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)
Subsample	Firms with unwanted outside directors only			
Dep. Variable	B&h returns$_t$			
Observations	15,289	15,289	7,537	7,537
R^2	0.1288	-0.0001	0.1321	-0.0044
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0040	-0.0035		
	(0.4398)	(0.1758)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0034***	-0.0072***		
	(0.0089)	(0.0000)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			-0.0266***	-0.0195
			(0.0087)	(0.1382)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0029**	-0.0012
			(0.0367)	(0.5010)
Dep. Variable	$ln(MVE_t)$			
Observations	15,289	15,289	7,537	7,537
R^2	0.3054	0.8754	0.2928	0.8692
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0237***	-0.0056		
	(0.0000)	(0.5135)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0172***	-0.0232***		
	(0.0000)	(0.0000)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			-0.0298**	0.0054
			(0.0376)	(0.7707)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0141**	-0.0123**
			(0.0481)	(0.0376)
Dep. Variable	Tobin's Q$_t$			
Observations	15,289	15,289	7,537	7,537
R^2	0.0752	0.1411	0.0747	0.1440
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0225***	-0.0146		
	(0.0003)	(0.1149)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0101***	-0.0272***		
	(0.0062)	(0.0000)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			-0.0173	0.0066
			(0.3850)	(0.7849)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0002	-0.0124
			(0.9812)	(0.1771)
Dep. Variable	ROE$_t$			
Observations	15,288	15,288	7,536	7,536
R^2	0.0224	0.0686	0.0230	0.0797
$\sum$***(unwanted dir., 25%$_{(y,i)}$, stayed)***	-0.0009	0.0022		
	(0.8384)	(0.4925)		
$\sum$***(unwanted dir., 25%$_{(y,i)}$, new)***	-0.0037	-0.0061***		
	(0.2422)	(0.0090)		
$\sum$***(unwanted dir., 10%$_{(y,i)}$, stayed)***			0.0119	0.0066
			(0.4069)	(0.3338)
$\sum$***(unwanted dir., 10%$_{(y,i)}$, new)***			-0.0120*	-0.0129**
			(0.0714)	(0.0168)
Year FE	yes	yes	yes	yes
Firm FE	yes	no	yes	no
Industry FE	no	yes	no	yes
Firm controls	yes	yes	yes	yes
Board controls	yes	yes	yes	yes
Takeover defense controls	yes	yes	yes	yes

Table 4.24: This table reports the results from five(six)-factor regressions (OLS) of equally weighted returns derived from pairs trading strategy. We calculate the four pairs trading strategies constructed with firms having more than 20%, 40%, 60% or 80% *unwanted* directors on a firm's board. A matched pair consists of a firm haven *unwanted* directors on the firm's board of directors and a firm form the same industry, having no *unwanted* directors on the firm's board and a indexed stock price time series with the lowest p-value within this subset of firms. The sample period is from 31/12/2001 through 31/12/2017. Standard errors are calculated using heteroscedasticity consistent covariance (HC1). Robust p-values are reported in parentheses, with ***, **, * denoting statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Strategies (share of *unwanted* directors)							
	20%		40%		60%		80%	
$Intercept$	0.0032***	0.0032***	0.0028	0.0027	0.0049**	0.0049**	0.0071***	0.0072***
	(0.0028)	(0.0030)	(0.1006)	(0.1020)	(0.0227)	(0.0232)	(0.0098)	(0.0094)
$Mkt-rf$	-0.0778*	-0.0722*	-0.1220*	-0.0889	-0.2000**	-0.1938**	-0.0703	-0.1085
	(0.0646)	(0.0818)	(0.0583)	(0.1535)	(0.0306)	(0.0428)	(0.5366)	(0.3242)
HML	0.0766	0.0863	0.0253	0.0827	0.1199	0.1308	-0.1038	-0.1700
	(0.1820)	(0.1577)	(0.7218)	(0.2465)	(0.2583)	(0.2388)	(0.5678)	(0.3415)
SMB	0.1212*	0.1188*	0.1179	0.1034	0.2720	0.2693	0.1689	0.1856
	(0.0817)	(0.0879)	(0.2374)	(0.2919)	(0.1172)	(0.1247)	(0.2933)	(0.2564)
CMA	-0.0716	-0.0840	-0.0802	-0.1540	-0.2760	-0.2899	0.6351	0.7203*
	(0.5863)	(0.5203)	(0.6019)	(0.2929)	(0.2171)	(0.1914)	(0.1047)	(0.0629)
RMW	-0.1734**	-0.1839**	-0.0233	-0.0855	0.1325	0.1207	0.0246	0.0964
	(0.0438)	(0.0370)	(0.8725)	(0.5552)	(0.5318)	(0.5704)	(0.9286)	(0.7319)
$Momentum$	0.0169		0.0999		0.0189		-0.1153	
	(0.6285)		(0.1221)		(0.7399)		(0.1468)	
Obs.	204	204	204	204	204	204	204	204
R^2	0.063	0.064	0.025	0.045	0.056	0.056	0.055	0.063
Adj. R^2	0.039	0.035	0.001	0.016	0.032	0.027	0.031	0.034

Appendix 4.B Variable Definitions

Table 4.25: Accounting data is from Compustat, stock price and return data is from CRSP, ownership data is directly taken from the form 13D filings, board and director data is from MSCI and voting data is from ISS. Variables descriptions regarding board and director data are adapted from the MSCI: GMI Ratings manual.

Variable	Definition
	Company variables
ln(Firm age)	The number of years since the company's first record date in the Compustat database for a given fiscal year.
ln(Firm size)	Natural logarithm of the company's total assets for a given fiscal year winsorized at the 1^{st} and 99^{th} percentiles.
B&h returns	The company's buy & hold stock return for a given fiscal year winsorized at the 1^{st} and 99^{th} percentiles.
Stock volatility	The company's annualized stock return volatility for a given fiscal year winsorized at the 1^{st} and 99^{th} percentiles.
ROE	The company's net income divided by its book value of equity for a given fiscal year winsorized at the 1^{st} and 99^{th} percentiles.
ROA	The company's earnings before interest, tax, depreciation and amortization (EBITDA) divided by its total assets for a given fiscal year winsorized at the 1^{st} and 99^{th} percentiles.
MTB	The company's market value of equity divided by its book value of equity for a given fiscal year winsorized at the 1^{st} and 99^{th} percentiles.
Leverage	The company's total debt divided by its total assets for a given fiscal year winsorized at the 1^{st} and 99^{th} percentiles.
Tobin's Q	The company's market value of equity plus its book value of total assets minus its book value of equity divided by its book value of total assets for a given fiscal year, winsorized at the 1^{st} and 99^{th} percentiles
CapEx	The company's capital expenditures (CapEx) divided by its total assets for a given fiscal year winsorized at the 1^{st} and 99^{th} percentiles.
R&D	The company's research and development expenditures (R&D) divided by its total assets for a given fiscal year winsorized at the 1^{st} and 99^{th} percentiles.
Active ownership	Total active ownership as filed by a form 13D(/A) filing by the end of the fiscal year winsorized at the 1^{st} and 99^{th} percentiles.
Classified board	Indicator variable, which takes the value one if the company has a board voting structure where directors stand for re-election on a staggered schedule within a fiscal year.

Business combination provision	Indicator variable, which takes the value one if the company has a business combination provision that prohibits the company from engaging in a merger or in any other extraordinary transaction with a person or an entity that owns a specified percentage of the company's stock for some period of time after the shareholder acquires the threshold amount within a fiscal year.
Constituency provision	Indicator variable, which takes the value one if a company has a provision that allows (or in the case of Connecticut, requires) a board to take into account the interests of non-shareholder constituencies such as employees, communities, customers and suppliers when making decisions, including decisions regarding the control of the company, within a fiscal year.
Cumulative voting	Indicator variable, which takes the value one if shareholders have the right to cast one vote per share times the number of directors to be elected, and distribute those votes between the candidates for director in any proportion within a fiscal year.
Dual class stock	Indicator variable, which takes the value one if the company offers multiple classes of common stock within a fiscal year.
Fair price provision	Indicator variable, which takes the value one if the company has a provision in its charter or bylaws requiring a higher voting threshold to approve, or prohibiting outright, a business combination that does not satisfy requirements as to minimum offer price and procedure within a fiscal year.
Poison pill	Indicator variable, which takes the value one if the company has a plan in place, in case that a hostile bidder acquires a threshold amount of the company's stock, to increase voting rights of shareholders, which massively dilutes the bidder's holdings and makes it prohibitively expensive for the bidder to complete the acquisition, within a fiscal year.
Shareholder fill vacancy	Indicator variable, which takes the value one if shareholders have the power to fill vacancies on the board that arise between regular annual meetings within a fiscal year.
Board size	Number of directors on the company's board of directors for a given fiscal year, winsorized at the 1^{st} and 99^{th} percentiles.
Board age	Median age of all directors on the company's board of directors for a given fiscal year, winsorized at the 1^{st} and 99^{th} percentiles.
Board tenure	Median tenure of all directors on the company's board of directors for a given fiscal year, winsorized at the 1^{st} and 99^{th} percentiles.
Board outside directors	Number of outside directors on the company's board of directors for a given fiscal year, winsorized at the 1^{st} and 99^{th} percentiles.
Director variables	
Outside director	Indicator variable, which takes the value one if the director is classified as independent of the company within a fiscal year.

Attendance	Indicator variable, which takes the value one if the director failed attendance standards (i.e. attending at least 75% of board meetings) on the respective company's board within a fiscal year.
Problem director	Indicator variable, which takes the value one if the director has been personally involved, as a director or an executive, in one or more corporate bankruptcies, major litigation and regulatory infractions, major accounting restatements and other corporate scandals, or has served on compensation committees that have approved particularly egregious CEO compensation packages, or other similar circumstances.
Director ownership	Share of common shares outstanding owned by a given director as reported in the most recent proxy filing.
Director tenure	Number of years the directorship has been active.
Director age	Age of a given director as reported in the most recent proxy filing.
Director gender	Indicator variable, which takes the value one if the given director is male.
Busy director	Indicator variable, which takes the value one if the given director is an active director on 3 or more boards.
Any CEO	Indicator variable, which takes the value one if the given director is an active CEO of another company.
Founder	Indicator variable, which takes the value one if the given director is also the founder of the given company.
Company CEO	Indicator variable, which takes the value one if the given director is the CEO of the given company.
Military	Indicator variable, which takes the value one if the given director has a military background. The variable is constructed from the name's prefix.
Professor	Indicator variable, which takes the value one if the given director holds a title of professor. The variable is constructed from the name's prefix.
Ph.D	Indicator variable, which takes the value one if the given director holds a Ph.D. The variable is constructed from the name's prefix.
Committee lead	Indicator variable, which takes the value one if the given director is the chairman of any committee.
Committee non chair	Indicator variable, which takes the value one if the given director is the chairman of any committee.
ISS recommendation	Indicator variable, which takes the value one if the ISS recommends voting "for" a director in its ISS proxy research report.
%-for votes	*for votes* divided by the sum of all votes cast (*for votes+withhold votes+against votes*).
unwanted director, $25\%_{(y,i)}$	Indicator variable, which takes the value one if a given director receives less *%-for votes* than the 25^{th} percentile in the respective year and industry (based on Fama and French's 48 industry classification).

unwanted director, $10\%_{(y,i)}$	Indicator variable, which takes the value one if a given director receives less *%-for votes* than the 10^{th} percentile in the respective year and industry (based on Fama and French's 48 industry classification).
unwanted dir., $25\%_{(y,i)}$, stayed	Indicator variable, which takes the value one if a given director is not only an unwanted director (unwanted director, $25\%_{(y,i)}$ takes one), but also received less *%-for votes* than the 25^{th} percentile in the prior year.
unwanted dir., $10\%_{(y,i)}$, stayed	Indicator variable, which takes the value one if a given director is not only an unwanted director (unwanted director, $10\%_{(y,i)}$ takes one), but also received less *%-for votes* than the 10^{th} percentile in the prior year.

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