The Nature Of Chapter-22 Debtors - *Forecasting Bankruptcy Recidivism Through a Novel Distress Predictor Model* *

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Abstract

This paper investigates the determinants of bankruptcy recidivism in U.S. courts using a sample of large Chapter 11 cases. We develop, through a series of logistic regressions, a novel distress predictor model that provides insights into variables that are critical to predicting bankruptcy recidivism. We find that high leverage in the capital structure, at the point of bankruptcy emergence, is the single-most significant determinant of bankruptcy recidivism. Low asset size and strong GDP growth prior to the initial bankruptcy also play a key role in predicting recidivism. We don't find evidence of ownership having a significant impact on recidivism rates, although there is some indication that activist investors fare better than lenders when in control.

Key Words: Bankruptcy, Restructuring, Debt

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Acronyms

DPM distressed predictor model

LoPucki BRD UCLA Lynn M. LoPucki Bankrutpcy Research Database

LBO leveraged buyout

MDA multiple discriminant analysis

PACER Public Access to Court Electronic Records

PE private equity

VIF variance inflation factor

1 Introduction

The legal processes of bankruptcy reorganization and liquidation have been a well trodden and often familiar path for American institutions. A 'bankruptcy' refers to a situation when a company's liabilities exceed the going concern value of its assets, necessitating a petition to either reorganize (Chapter 11) or liquidate (Chapter 7) its assets in line with the U.S. Bankruptcy Code. Companies file for bankruptcy due to a combination of economic distress, which concerns viability, and financial distress, which concerns leverage, profitability, liquidity, and asset size (Tashjian, 2017). Interestingly, some companies file for bankruptcy more than once, burdening the legal system and further accruing economic costs to their stakeholders. Bankruptcy recidivism, as this phenomenon is described, is the focus our paper; in the following pages we analyse its determinants and construct a model that predicts its occurrence.

Initiated by either the debtor or creditor groups, companies enter a Chapter 11 proceeding after all other out-of-court methods are attempted, in order to restructure their liabilities with relevant claimants. This legal process grants the debtor 'automatic stay', preventing collection and enforcement actions by creditors until a reorganization plan has been finalised by the court. It additionally allows companies the ability to restructure their assets (through asset sales), and liabilities (through restructuring) to better meet their financial obligations. If the reorganization plan is approved by the class of impaired voters and the court, the company successfully emerges from bankruptcy. However, in the event that no agreement is reached, a firm can confirm a 'liquidating' Chapter 11 plan or convert the petition to a Chapter 7 process. The premise behind bankruptcy law follows that, an entity should exclusively be allowed to reorganize and operate if its going-concern value is greater than its liquidation value. Otherwise, liquidation is the preferred alternative (Altman et al., 2019).

Ultimately, we argue, the efficiency of the reorganization process should be measured by the proportion of firms that subsequently fail after restructuring. We define 'failures' of the bankruptcy process as companies that re-file for bankruptcy, in contradiction to the aims of the U.S. Bankruptcy Code. In this paper, we study the existence of 'failure' in the bankruptcy system by analysing re-filers[1] and examining the potential determinants of bankruptcy recidivism. Altman (1983) first coined the term "Chapter 22" to refer to companies that had filed twice; we borrow this term as a catch-all to

[1]**Nomenclature**: Here-in, re-file and recidivism are used interchangeably to refer to repeat Chapter 11 or subsequent Chapter 7 filings. Altman's 'Chapter 22' is also utilised as a catch-all term for re-filers when comparing against Chapter 11 single-filers.

apply to firms that are classed as multi-filers (Chapter 22s, 33s and 44s). (See Altman et al. (2009), Hotchkiss and Mooradian (1997), and Altman et al. (2019) for a detailed guide to Chapter 22s and the bankruptcy process).

Bankruptcy recidivism in U.S. courts is a well documented phenomenon, with Altman et al. (2019) presenting evidence of consistent re-filing activity between 1984 and 2017 from a sample of large public U.S. bankruptcies. From their bankruptcy dataset, 290 firms filed twice, while in total 312 firms (8% of the sample) re-filed at-least once. Similarly, Hotchkiss and Mooradian (1997) report that almost 15% of their bankruptcy sample re-enter Chapter 11, while LoPucki and Whitford (1992) observe a 32% re-filing rate in their study of larger Chapter 11 filings. There remains some variance in the frequency of bankruptcy recidivism amongst studies, perhaps due to timing relative to the market cycle, but this issue continues to prevail across the literature. We view this recurrence of recidivism as a failure of the bankruptcy code, from both a legal and financial perspective. In the presence of liquidation costs (Shleifer & Vishny, 1992) and agency costs (Mooradian, 1994), repeated bankruptcies present material financial costs to debtors and impaired creditors. In a meta analysis conducted by Hotchkiss et al. (2008), direct costs of bankruptcy were found to be in the range of 1-10% of asset book value, while indirect costs were reported to be in the range of 10-20% of asset book value.

Existing literature suggests a few reasons for recidivism. Gilson (1997) provides evidence that bankrupt companies emerge from Chapter 11 highly leveraged relative to industry peers, while at the same time the majority of emerging companies under-perform their industry peers several years after bankruptcy (Hotchkiss et al., 2008). The excessive leverage of companies after Chapter 11 may be driven by over-optimistic management expectations and financial forecasting, as described by Michel et al. (1998). The governance structure of a company, and in particular its ownership, is also shown to play an important factor in post-bankruptcy performance, with Hotchkiss and Mooradian (1997) presenting evidence showing that the percentage of companies with negative operational performance is lower when vulture investors retain influence. Lastly, Altman (2014), when discussing his dataset in the context of recidivism, suggests that operating issues, more-so than high leverage, are the primary cause of re-filing, in light of survey data.

The high rate of recidivism occurs despite the so-called feasibility requirement of Chapter 11 bankruptcies. According to 1129(a)(11) of the Bankruptcy Code, bankruptcy courts should assess whether a plan of Chapter 11 reorganisation is feasible and unlikely to lead to further reorganisation. However, in reality, courts only review the supporting evidence presented by the debtor without conducting any independent analysis. As a result, the review process rarely finds that the plan of reorganisation is not feasible

(Winikka, 2006). This issue of insufficient information leading to poor liquidation decisions (which may lead to recidivism), is also mirrored in creditor decisions, as noted by Kahl (2002). However, existing research (Altman, 2014; Altman et al., 2009) on bankruptcy recidivism shows a significant difference between the 'Z-Score' of re-filing and non-refiling companies just after emergence. This suggests that there may be distinctive characteristics that can help to differentiate between Chapter 11 and Chapter 22 companies, *even prior* to bankruptcy emergence.

Therefore, in our paper, we study companies prior to emergence from their initial bankruptcy, examining the differences between companies that re-file within five years and those that don't. We examine the impact of not only financial variables, as is common practice, but also ownership, legal and economic variables. We base our study on the UCLA Lynn M. LoPucki Bankrutpcy Research Database (LoPucki BRD), which solely focuses on the largest U.S. bankruptcies. Unique to our paper, we use financial projections and valuations that are part of disclosure statements to Chapter 11 plans of reorganization. We also draw on the vast array of legal variables in the LoPucki BRD and, for instance, study the impact of equity committees and court selection. Furthermore, we collect proprietary data on post-bankruptcy ownership to study how different owners (e.g., Private Equity, Activist, or Lenders) affect refiling rates. This combination of variables hasn't previously been studied in published academia, allowing us to contribute to the vast field of bankruptcy research. Lastly, we develop a novel distress predictor model tailored to identifying recidivists, that presents promising results with significant accuracy. We comment on its predictive performance and attempt to illustrate that recidivism can be predicted prior to emergence from bankruptcy.

The major findings of our paper can be briefly summarised as follows: First, the financial factors used for predicting bankruptcies are also relevant for predicting recidivism, with high leverage being the most critical determinant of re-filing. Second, GDP growth before bankruptcy is highly influential, with companies going bankrupt in a positive macroeconomic environment being more likely to re-file. Third, we don't find evidence of ownership having a significant impact on recidivism rates, although there is some indication that activist investors fare better than lenders when in-control of the company.

The outline of our paper is as follows: Section 2 reviews the existing literature on the determinants of bankruptcy recidivism and bankruptcy prediction. Section 3 describes the data collection process, presents a rationale for the variables analysed, and provides an overview of their presence in our sample. Section 4 discusses the logistic regression model, its assumptions, and the fundamentals of prediction. Section 5 examines the financial, legal, and ownership determinants of bankruptcy recidivism, and presents the estimated effects of the variables used. Section 6 proposes a generalizable specification of a novel distressed predictor model (DPM) for predicting recidivism. Finally, Section 7 summarises the findings of our paper.

2 Literature Review

In this chapter, we provide readers with a comprehensive summary of literature that we build upon in our paper. First, we discuss literature on bankruptcy recidivism and its determinants, examining the financial position of debtors; ownership and stakeholder dynamics; and the court process and bankruptcy outcomes. We then review the literature on bankruptcy prediction, focusing on the 'accounting approach' to forecasting bankruptcy.

2.1 Bankruptcy Recidivism

The high rate of Chapter 22 filings is a commonly observed phenomenon, with several early studies of post-bankruptcy performance demonstrating the incidence of reorganization after an initial Chapter 11 process. Hotchkiss (1995) presents evidence from her sample, where c.32% of firms restructure again either through an in-court or out-of-court process. Similar findings have been provided by LoPucki and Whitford (1992), Gilson (1997), and Tashjian (2017). Altman and Branch (2015) also suggest that c. 18% of debtors who emerge as continuing independent entities under Chapter 11 ultimately re-file for bankruptcy, with the majority doing so within five years.

There are potentially numerous explanations for the high rate of recidivism observed, given the complexities of financial and economic distress. Certain exogenous events, such as economic shocks and unforeseen regulatory actions, may also push a firm towards distress and subsequent bankruptcy. Altman et al. (2019) note that among the Chapter 22s studied, there are many debtors from industries with cyclical volatility and high sensitivity to macroeconomic conditions, such as manufacturing and transport, reflecting the high economic risk faced by these companies. While companies are often at risk of financial distress / bankruptcy due to a short-term inability to meet their liabilities, economic distress due to an unsustainable operating model, often observed through lagging operating income in the years prior to filing, increases the likelihood of recidivism materially (Tashjian, 2017). A combination of these failures frequently occurs within the first five years after Chapter 11 emergence, and additional factors likely contribute to the recurrence of distress (Altman, 2014).

2.1.1 Financial Position and Financial Performance of Debtors

An often discussed determinant of recidivism is excess leverage after an initial Chapter 11. Many firms fail to mitigate their debt burdens under their initial plan of reorganization, resulting in continued risk of financial or economic distress. The rationale behind these actions stems from the simple trade-off between bankruptcy costs and the tax benefits of additional debt, and represents one of the cornerstones of corporate financial theory (Altman, 2014). Altman and Branch (2015) provides evidence of how, in a study of 172 firms observed from 1990-2004, leverage remained high relative to each company's industry, even after their debt burdens were mitigated through restructuring. Gilson (1997) notably observed that leverage remained high after both out-of-court restructurings and Chapter 11 reorganizations. He calculated the median leverage ratio of firms in Chapter 11 between 1980 and 1989, and found that leverage was significant relative to industry expectations. Therefore, the presence of excessive leverage after bankruptcy may construe a refiling risk for a recently emerged Chapter 11 debtor. In Altman (2014), the leverage of Chapter 22 firms in his sample was approximately three times greater than Chapter 11 single-filers, giving some support to the notion of leverage increasing recidivism risk.

Furthermore, Altman (2014) also identified operational issues in his Chapter 22 sample, with these companies being inferior to Chapter 11 firms with respect to profitability, leverage, liquidity, and asset size. The observed leverage and profitability metrics were significantly divergent between the Chapter 22 and Chapter 11 samples. Operational issues were also cited as reasons for recidivism by LoPucki and Whitford (1992), with their study of bankrupt firms identifying operational issues as the primary factor behind Chapter 22 filings. Several studies assessed operational metrics (cash flows and profitability) relative to comparable firms. In a meta analysis of recidivism and post bankruptcy performance literature, Altman (2014) observed that more than 66% of firms emerging from bankruptcy under-performed peers over a five year time horizon; related articles (eg. Hotchkiss (1995)) suggested that c.40% showed poor operating performance three years after bankruptcy emergence. We hypothesize that the performance of companies that initially go bankrupt is already much lower than the population average, and that this under-performance persists even after multiple Chapter 11 filings. Another potential explanation is that the management of distressed firms promote highly optimistic cash flow forecasts, allowing debtors destined for liquidation to successfully emerge from Chapter 11 reorganization (Hotchkiss, 1995). Michel et al. (1998) illustrates that financial projections in the reorganization plans of Chapter 22 companies *during their first Chapter 11* are typically *overstated*, especially when compared to single filers. This would naturally increase the occurrence of recidivism, as these 'over-optimistic' firms are assumed to be unsustainable and are likely unable to meet their debt obligations unless significant changes are made.

Within bankruptcy literature, a pertinent distinction is made between firms that filed due to financial distress and economic distress, with each having different implications for recidivism. Tashjian (2017), in their seminal paper discussing bankruptcy recidivism, identify the *type of distress* (financial or economic) when entering Chapter 11, and find evidence that economic viability (calculated primarily with operating profit) positively affects the likelihood a firm will emerge from bankruptcy and negatively affects the likelihood that a firm that reorganizes will subsequently re-file. In their sample of 831 large, publicly traded firms that file for Chapter 11 between 1991 and 2008, less than 20% of the firms classified as primarily economically distressed reorganize and emerge, while over 60% of primarily financially distressed firms do so.

2.1.2 Ownership & Stakeholder Dynamics

In bankruptcy literature, ownership is regarded as an important determinant of post-bankruptcy performance. This extends not only to the ownership of the firm after Chapter 11, but also to the ownership of its debt. To begin with, material changes to the share holder structure are common during the Chapter 11 reorganization process. Gilson (1990), in his paper on change in ownership in defaulting firms, provides evidence from 61 Chapter 11s that c.80% of the common stock is distributed to creditors during the restructuring process. This implies a change in the level of concentrated ownership, and control, in favour of the company's senior and unsecured lenders. The distribution of equity in the restructured firm to pre-petition creditors continues to be typical of Chapter 11 reorganizations, while significant distributions to pre-petition equity holders are rare. Furthermore, the presence of activists and other investors in bankruptcies is commonplace; a study by Ivashina et al. (2016) illustrated that activist investors, including hedge funds, are the largest net buyers of claims in bankruptcies, with a preference for the fulcrum security in the capital structure. An activist investor benefits from buying the fulcrum claim as it grants them influence over the restructuring process, with the ability to block a plan of reorganization. Hotchkiss and Mooradian (1997), in an early study on the behavior of distressed debt investors, found that "vulture" investors gained control of c.16% of their sample of 288 firms over a thirteen year period. The influence of these investors has become even more prevalent over time; Jiang et al. (2012) show that close to 90% of their sample of 474 large Chapter 11 cases from 1996 to 2007 have publicly observable involvement by hedge funds. (please refer to Moyer et al. (2012) and Moyer (2004) for a practitioner's guide to distressed investing and other relevant activist strategies).

Furthermore, the rise in defaults of companies owned by private equity funds has led to an increase in the activity of private equity investors during bankruptcy (Hotchkiss et al., 2021). If a private equity (PE) fund's original equity stake is diluted or eliminated during Chapter 11, the PE sponsor can continue to maintain its control of the distressed firm via an equity infusion as part of the restructuring process. Evidence from Hotchkiss et al. (2021) also shows that PE sponsors actively pursue ownership of distressed firms not in their portfolio, taking control of c.19% of defaulted companies in their study.

In light of this investor activity, a significant component of literature on recidivism studies the impact of ownership on post-bankruptcy performance. Hotchkiss and Mooradian (1997) find stronger post-bankruptcy performance when hedge funds are active in the governance of reorganized firms; Jiang et al. (2012) find that the participation of hedge funds is associated with a higher probability of emergence and higher payoffs to junior claims; Lim (2015) finds that hedge fund involvement in the restructuring process is associated with greater debt reduction relative to other bankruptcies. Ellias (2016) measures the intensity of the litigation campaigns embarked upon by investors in junior claims; he finds that "junior activism" is associated with higher values of reorganized firms. The positive role of these investors in the corporate governance of distressed firms is consistent with broader research in corporate finance, which demonstrates that corporate control aids in improving the management of under-performing firms (Jensen, 1986). We additionally hypothesize that the presence of activists / hedge funds within junior claims is a signal that the firm has a high going-concern value relative to its capital structure, as the senior claimants aren't impaired; if senior tranches were impaired, junior claimants would likely be 'wiped-out' and their claims would be written down, with little power to appeal. Thus, there may be both endogenous and exogenous effects involved.

Hotchkiss and Mooradian (1997) observe that the involvement of distressed debt investors is strongly linked to post-bankruptcy success in their sample of defaults from 1980-1993. In the group with no identifiable vulture involvement, 1/3 recorded negative operating income one year post-bankruptcy; this was distinctly different to the group with vulture activity, where only 1/10 recorded negative operating income after bankruptcy. Moreover, evidence of active ownership/governance by an activist, and in particular, board presence and control, is associated with the best performance post-emergence (relative to pre-bankruptcy). On the other hand, in cases where the vulture/activist remains passive, Hotchkiss and Mooradian (1997) find that performance doesn't diverge significantly from the group without vulture presence. As mentioned in earlier commentary, we must note that the results presented, while interesting, may suffer from endogeneity, as the level of 'activism' observed is correlated with how much control vultures capture during the restructuring process. This is likely to be low in cases of senior lender control, which would also imply a more impaired capital structure with lower going-concern value.

With respect to the impact of private equity investors on distressed and bankrupt firms (vis-à-vis recidivism), we find that the literature typically acknowledges the harm of higher leverage from leveraged buyouts (LBOs), and the benefit of active management by private equity investors. Hotchkiss et al. (2021) study a set of 2,151 firms that borrow in the leveraged loan market between 1997 and 2010, and find that PE-backed firms have higher leverage in their capital structure and default more frequently. After controlling for leverage, the paper suggests that the default probability between the two groups is identical, and that PE-backed firms avoid bankruptcy court more often relative to other highly leveraged firms. Jensen (1989), alongside others, has identified the 'discipline of high leverage' and monitoring by PE investors as some of the key benefits of LBOs. Further work by Cohn et al. (2022) provides positive evidence that PE acquirers create value by improving access to financing (equity and debt) for key investments, while improving operational performance; financial engineering is shown to play a limited role.

Senior creditors also influence the governance of firms. Academic research demonstrates that when firms violate covenants, the control rights of senior lenders influence firms' actions in ways that can increase value. Nini et al. (2012) examine 3,500 incidences of covenant violations from a sample of firms between 1997 and 2008. Their study captures that covenant violations are subsequently followed by sharp reductions in leverage, and that operating performance improves, which suggests intervention by senior lenders is associated with a turnaround in performance. However, in relation to bankruptcies, conflicting interests of senior lenders may harm post-emergence performance. K. M. Ayotte and Morrison (2009) study a sample of large bankruptcy cases filed during 2001 and argue that there is "pervasive" secured creditor control, and also that a sale of the company is more likely when secured lenders are over-secured (little incentive to participate in the upside achieved through operational improvement).

Lastly, conditional upon a default, the identity of claimants impacts a firm's ability to renegotiate its debt, potentially leading to recidivism. Debt under dispersed ownership is subject to holdout problems and hence more difficult to renegotiate in out-of-court processes (Gilson et al., 1990). The most recent study to examine this is by Demiroglu and James (2015), who analyse 344 debt restructurings from 2000 to 2012. Confirming earlier studies, the authors find that firms are most likely to be able to restructure out of court when negotiating with a single creditor. Firms that rely on institutional loans, with dispersed ownership, are more likely to restructure in court.

2.1.3 Court Process & Bankruptcy Outcomes

Papers discussing the legal determinants of bankruptcy emergence are well-published, with most literature focusing on the Chapter 11 process and format of the reorganisation plan. Variables such as venue choice, judge disposition and the appointment of committees, among others, are shown to have an impact on successful bankruptcy emergence (LoPucki & Doherty, 2015). There is clearly a belief that the bankruptcy process can have a large impact on the post-bankruptcy outcomes of firms, as the famous debate on court competition for large cases illustrates (K. Ayotte & Skeel Jr, 2006; R. S. Lee, 2011; LoPucki, 2005; LoPucki & Doherty, 2002). However, the links between legal variables and bankruptcy recidivism are unsubstantiated from a theoretical perspective, with limited published research on the topic.

With respect to venue choice, LoPucki (2005) argue that this practice of "forum shopping" enables firms to choose debtor-friendly venues, leading to inefficient reorganizations. Others argue that sophisticated debtors choose courts that have more expertise in dealing with complex cases. Between 1990 and 2017, more than half of U.S. public firms with at least $50 million in book assets filed their petitions in only two courts: the U.S. Bankruptcy courts for the District of Delaware and Southern District of New York (Altman et al., 2019). In particular, Delaware has been recognized for its ability to quickly process pre-packaged and pre-negotiated bankruptcies (K. Ayotte & Skeel, 2004), while the Southern District of New York (SDNY) has been recognized as being more "management friendly" (Hotchkiss, 1995). There is some debate as to whether venue choice has an impact on debtors in bankruptcy, given the selection bias involved and the complex capital structures of firms filing in Delaware. K. Ayotte and Skeel Jr (2006) argue that the frequency of recidivism in Delaware and SDNY may be correlated with the number of complex Chapter 11s that are filed in these forums.

Judge disposition (experience) may also have some impact on the post-bankruptcy success of Chapter 11 filers. A few studies provide empirical evidence that bankruptcy case characteristics are independent of judge characteristics (e.g., Bernstein et al. (2019); Chang and Schoar (2013); and Iverson et al. (2018)). However, these studies also examine the effect of judges' experiences and preferences on bankruptcy outcomes. They find that judges' on-the-bench experiences have a strong impact on bankruptcy duration, the probability of emergence, and the debtor's post-emergence performance, and that their pro-debtor preferences strongly explain the propensity to grant or deny certain motions.

With respect to creditor committees, the U.S. Trustee is responsible for the appointment of an official committee to represent the interests of unsecured creditors (the "UCC"). The UCC ordinarily consists of unsecured creditors holding the seven largest unsecured claims, and files objections with the court for actions taken by the debtor that may negatively affect enterprise value and debt recovery. Academic studies show that their presence occurs in over 30% of the largest Chapter 11 cases filed from the late 1990s to early 2010s (Jiang et al. (2012); Wang (2021)). Equity committees have a smaller track-record, occurring in less than 10% of Chapter 11 cases of large U.S. public firms in the past two decades. The appointment of both an equity committee and unsecured creditor committee considers several factors including whether there is any substantial likelihood of a meaningful distribution to the claimants, which may be unlikely for a more severely impaired debtor. Thus their presence may act more as a signal for the level of impairment, as opposed to a variable with actual impact on post bankruptcy performance, and may contain some endogenous effects.

2.2 Bankruptcy Prediction

The issue of predicting bankruptcy is well researched. Since Altman (1968) came up with his famous Z-Score, hundreds of papers have been written on the topic, with three prominent approaches taking the lead: accounting, market, and blended. As the nomenclature suggests, accounting approaches, e.g., Z-Score, rely solely on accounting data from the company's financial statements. Market approaches, i.e. structural and reduced-form models, utilize the market data of companies' securities and equity. Finally, blended approaches, e.g., hazard model, combine accounting and market data to increase prediction accuracy. As most bankrupt companies subsequently suspend the trading of their stock, the market and blended approaches are not relevant for our paper; we will thus focus only on accounting approaches.

As introduced by Altman (1968), the accounting approach to predicting bankruptcy is a fairly straightforward method in which various financial ratios are used to predict bankruptcy occurrence within a one year horizon. In his seminal work, Altman used the following ratios - Working Capital/Total Assets, Retained Earnings/Total Assets, EBIT/Total Assets, Market Value of Equity/Total Liabilities, and Sales/Total Assets. He then used multiple discriminant analysis (MDA) to estimate how bankrupt companies differ from non-bankrupt companies. The resulting coefficients, when combined, created a gauge of credit strength called the Z-Score. The Z-Score was later adapted by Altman et al. (1984), who constructed the Z"-Score for estimating the bankruptcy probability of non-public companies. The Z"-score used the book value of equity instead of the market value, and discarded the fifth ratio – Sales/Total Assets, which had not performed well for non-manufacturing firms.

Since Altman's seminal work in 1968, the key factors for predicting bankruptcy remain the same: measures describing the financial structure, financial performance, and current liquidity, with the addition of the size of the company's assets as proposed by Ohlson (1980). What has changed is the preferred methodological approach. MDA, a once prevalent approach, had fallen out of favor because of its flaws, i.e., the requirement of normally distributed predictors, the lack of intuitive interpretation, and the need for the same variance-covariance matrices of predictors for bankrupt and non-bankrupt firms. Instead of the MDA, researchers suggested different methods to rectify MDA's flaws and achieve higher efficiency. For example, Ohlson (1980) used the logistic regression model, which provided a clear interpretation of the probability of bankruptcy, and alleviated many of the MDA's issues. Other authors used different models based on artificial intelligence, with the most popular approach being artificial neural network models which were introduced to bankruptcy modeling by Odom and Sharda (1990); support vector machines used by Shin et al. (2005); and decision trees used by K. C. Lee et al. (1996). For a complete review of the models used for bankruptcy prediction, please see Alaka et al. (2018).

An important challenge in bankruptcy prediction is predicting bankruptcies over longer time horizons. In most cases, models are built to predict bankruptcy over a one-year period, using one-year static data, with their prediction accuracy rapidly declining over longer periods (Altman et al., 2020). Predictions over longer terms are naturally difficult to conduct, as the differences between companies may decrease over a long-enough time horizon, inhibiting the identification of recidivists. Furthermore, long-term changes in the economic environment may be fatal for companies that would otherwise survive under normal conditions. Researchers found that prediction accuracy for longer time-horizons can be improved by using data from multiple periods (Altman et al., 1977; Aziz et al., 1988; Dambolena & Khoury, 1980). In addition, recent research by Du Jardin (2015) suggests that companies have different failure processes that further improve prediction accuracy, when correctly implemented into the model. However, despite the collective effort, a certain drop in prediction accuracy is expected (see Du Jardin (2017) for a review of prediction accuracy of different studies for a one-to-five-year period).

3 Sample Construction

This paper conducts an empirical analysis on the post-bankruptcy outcomes of 144 U.S. companies, relying on data collected from court dockets prior to bankruptcy emergence. In particular, we study the impact of financial, legal, ownership, and economic determinants on the occurrence of bankruptcy recidivism. Our universe includes all large Chapter 11 debtors that filed for bankruptcy after December 2003, and emerged from their initial petition before December 2015. All companies in the sample were public prior to filing, and we supplemented information from a variety of data bases – many requiring manual collection efforts. With respect to the identification of single/multi-filers, we chose a five-year window, after emergence from Chapter 11, to observe recidivism. As a result, our sample covers initial Chapter 11 emergence from 2003-2015, and captures instances of Chapter 22s up-to 2020. Given the five-year window, we do not capture any multi-filers that emerged before 2003. Of the final sample space of 144 bankruptcy cases, 34 companies re-filed within 5 years after emerging from Chapter 11, while 110 companies survived for at least 5 years. Table 1 summarizes the overall data attrition during sample construction.

Table 1: Sample Construction Summary Table

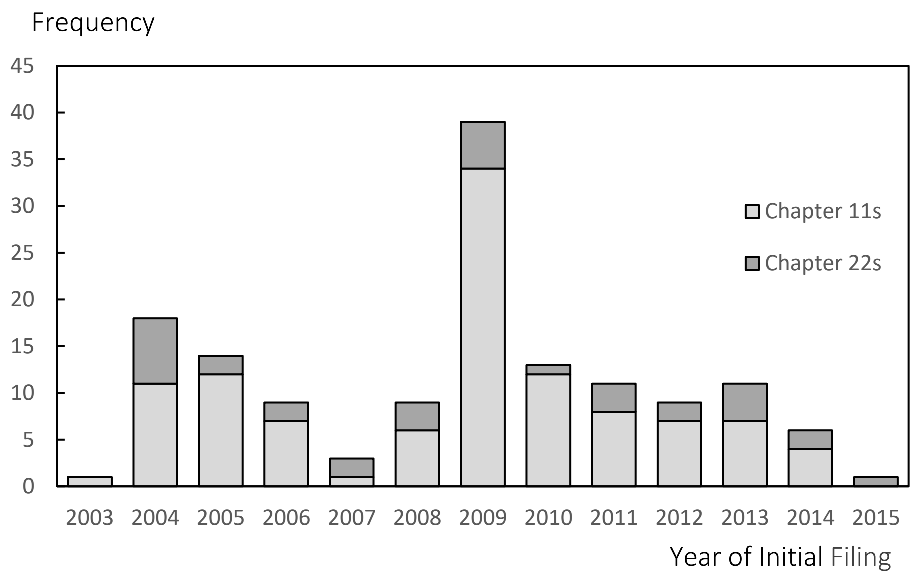
Criteria	Sample Size
LoPucki Bankruptcy Database	**1215**
Company Emerged from Bankruptcy	815
Study of Initial Bankruptcies up-to 2015	668
Disclosure Statements are Publicly Accessible	219
Industries Excluding Finance and Real estate	204
No Major 363 Asset Sale Recorded	179
Sufficient Information Provided in Disclosure Statement	144
Final Sample	**144**

3.1 Sample of U.S. Chapter 11 Firms

We base our sample on the UCLA Lynn M. LoPucki Bankrutpcy Research Database (LoPucki BRD) universe, which provides up-to date information on public bankruptcies filed in U.S. courts since 1979. To be listed in the LoPucki BRD, companies filing for bankruptcy must have pre-petion assets higher than \$ 100 million in 1980 USD, (*\$330 million in 2022 USD*). Additionally, the companies need to have been public at least 3 years prior to filing for bankruptcy.

At the time of writing, the LoPucki BRD universe consisted of 1215 cases. To arrive at our final sample, several criteria were applied to the LoPucki BRD, as presented in Table 1. All Chapter 7 Liquidations (c. 400) were excluded from our sample, as we solely focused on firms that emerged from bankruptcy. We further excluded 147 cases as we restricted the scope of our study to firms that emerged up to 2015, in order to have a representative five year post bankruptcy period for all cases. Our 5 year study range stems from a seminal paper by Altman et al. (2009), where it was found that 89% of the Chapter 11s studied re-filed within 5 years, with this range later utilized in their model. Subsequently, we define 'success' in the context of Chapter 11 emergence as companies which don't refile within 5 years. Altman (2014) provides a more nuanced discussion regarding the period of study after bankruptcy emergence; while the majority (56%) of firms in his sample file again less than five years after emerging from their prior bankruptcy, 44% re-file after five years. Noting this variance in recidivism, Altman offers some resistance to our idea of success (no bankruptcy filing within 5 years of emergence); however, as this is not argued against entirely, it doesn't remain a point of contention for our paper.

Figure 1: Bankruptcy Outcomes by Year of Initial Filing



On account of a lack of publicly accessible data on Public Access to Court Electronic Records (PACER) prior to December 2003, 449 bankruptcy cases were excluded from our sample. From this, we excluded bankruptcies of financial, insurance and real estate institutions (15 cases), due to the disproportionately asset heavy nature of these industries, based on methodology utilised by Bryant (1996). A further 26 cases were dropped in relation to having sold all or substantially all of their assets in 363 sales. Lastly, we excluded 34 companies that lacked sufficient financial information, or were in fact Chapter 11 liquidations (this was simply classified as a Chapter 11 within the LoPucki BRD). The final sample consists of 144 companies that initially defaulted between 2003-2015. Out of the 144, 34 companies (23.6%) filed for bankruptcy again within 5 years (i.e. Chapter 22s), while 110 companies (76.4%) continued to operate (i.e. Chapter 11s that emerged and didn't re-file). Figure 1 summarises the bankruptcy cases in our sample by the year when the initial bankruptcy was filed. The low number of cases in 2003 is explained by the PACER filings only being available from the end of 2003. On the other hand, the low number of cases in 2015 is explained by most 2015 filers emerging in 2016-2018, and as such being excluded from our sample due to lack of representative period.

3.2 Bankruptcy Process Data

The LoPucki BRD provides extensive background information on bankruptcy cases, including the date of filing, the type of filing (such as prepackaged, free-fall and pre-negotiated), and the outcomes and duration of the Chapter 11 process. From over 200 variables in the database, we chose 7 that had previously been studied by LoPucki and Doherty (2015) and had shown a statistically significant impact on bankruptcy survival, with the notion of testing their impact on bankruptcy recidivism. Namely, we selected variables describing: Chapter 11 approach by the debtors - *Free Fall*, *Pre-packaged*, and *Pre-Negotiated*; the presence of committees - *Unsecured Committee* and *Equity Committee*; planned sale of assets - *Planned Sale of Assets*; experience of the presiding judge - *Inexperienced Judge*; and if the debtor filed for bankruptcy in Delaware or the Southern District of New York - *Delaware or NY SD*. For a more thorough definition of the variables listed, please see Table 2.

3.3 Identifying Ownership

The S&P Capital IQ database and Reuters Eikon were utilised to collect information on company ownership at the point of emergence, and we cross-referenced this against court disclosure documents which listed the proposed reorganisation plan. This paper classifies investors into four categories, namely: (1) *Private Equity Investors*; (2)*Activist Investors*; (3) *Lenders*; (4) *Other Control*. The classification is summarized in Table 2. A similar exercise was conducted by Hotchkiss and Mooradian (1997), with some important distinctions being our classification of activists, and our inclusion of private equity investors and lenders within the scope of our analysis. Rather than utilising a database of know activists, as per Hotchkiss and Mooradian (1997), we specifically classified activists as funds that marketed a 'debt-for-control', 'special situations' or 'opportunistic credit' strategy, and utilised this investment vehicle when obtaining control or significant influence during the reorganisation process. There are generally two major types of distressed investors Gilson (1995). The first group focuses on debt-for-control investing. These investors, usually from private equity funds, typically pursue a "loan-to-own" strategy through which they identify and purchase the "fulcrum" security, with the intent of converting it to majority equity ownership in the emerged entity. These investors do not sell their equity stake immediately after restructuring, instead choosing to hold their position over three to five year investment horizon. They proactively get involved in corporate governance such as management and board selection and the business operations of the firm in reorganization and after. The second group of investors are typically hedge funds with expertise in trading distressed claims and managing the bankruptcy process. They do not aim for a majority equity stake but often seek profits through identifying under-priced claims, though they sometimes also adopt strategies to influence the reorganization process. Some investors within this group focus on purchasing and consolidating trade or other claims, and gain from resolving the coordination problems among dispersed creditors. In practice, while we have presented the two types of distressed investors here as distinct, the line can blur with hedge funds sometimes going for control and private equity firms sometimes focusing more on trading profits.

A highly intensive manual collection effort was undertaken to identify the investors involved and the strategy utilised in each case/investment. We analysed the published portfolio holdings of any PE funds observed, and also studied 13 D filings for hedge funds and activists to gain a clear perspective on the type of strategy utilised by the fund, in order to accurately classify it. When recording multi-asset managers or PE funds with multiple strategies, we went through the added step of identifying *which fund* (eg. special situations or corporate private equity) completed the investment. This level of granularity also separates our work from that of Jiang et al. (2012), who classified any alternative investment manager as an activist or Hedge Fund, regardless of whether the investor was using their private equity, public equity or debt strategy.

This paper views the actions and incentives of activists as being dissimilar to those of private equity investors, following the findings of Kaplan and Stromberg (2009), Altman et al. (2019) and Bebchuk et al. (2015); we subsequently aim to distinguish between these in our sample. We identify the investors at the fund or management company level, as this allows us to identify the relevant investor group in the target firms. To identify significant influence or control, we impose a cumulative 50% threshold on a group of similar investors, or if a single investor had over a 30% stake in the reorganised entity. In cases where an investor had less than 50% control, we often looked at filings and news on the bankruptcy, to identify if any investors were perceived as either leading the Chapter 11 negotiations or having a 'priority influence'. With respect to cases where 2 investors of different classes each had a stake over 30%, we examined board representation to determine overall influence. This stems from theory on ownership impact, where even a minority investor may have out-sized influence on management decisions, as is often seen in 'public activist' literature such as Bebchuk et al. (2015). Further support of our classification system can be observed in the work of Jiang et al. (2012), who follows a similar protocol, but imposes a significantly lower threshold of 2% of the shares outstanding for "significant" equity ownership, as stakes smaller than this are unlikely to be effective in influencing the reorganization process. We also classified a subset of the ownership data as 'other', applying it to instances where the companies were either targets of acquisition by industry competitors, or continued to operate under the original private ownership. Lastly, the majority of our sample group (48%) was classified as being under lender ownership. We believe 'simple lenders' require their own classification category, as they often have lower return and risk expectations, and are inexperienced in the management and operational improvement of companies. Thus unlike activists and private equity investors, they are likely to create far more dissimilar outcomes post-bankruptcy (refer to K. M. Ayotte and Morrison (2009) for a review of lender practices).

3.4 Firm-Level Financial Information

When designing this paper, one of our core ideas was to attempt to predict bankruptcy recidivists prior to their emergence from an initial Chapter 11. We hypothesized that if the difference between the group of Chapter 11 and Chapter 22 firms was significant after emerging from bankruptcy, as Altman et al. (2009) and Altman (2014) had shown, it may also be significant prior to bankruptcy emergence, i.e. before the confirmation of a plan of reorganization. However, firms going through Chapter 11 face significant changes to their capital structures and operational forms, and therefore, financial information about past performance, typically used for bankruptcy prediction, might not be relevant.

As observed in the largest bankruptcy cases studied in our paper, the valuations and forward looking financial projections of debtors are almost always prepared. This is as bankrupt companies have to provide claimants with adequate information to make an informed judgment based on 1125(b) of the Bankruptcy Code. The valuation of the bankrupt company, based-on management projections, plays a central role in the bankruptcy process as the valuation directs the distribution to claimants. Naturally, the different parties have divergent incentives and views with regard to the valuation. Senior creditors want the debtor's valuation to be underestimated, as the excess value over their claims will be distributed to junior creditors. Junior creditors, on the other hand, want the valuation to be overestimated, as it increases their distribution. Gilson et al. (2000) shows that the relative bargaining strength of different parties influences the valuation of the company. Though some distortion in valuation due to different incentives exists, it is unlikely that the valuation would be completely fabricated as the plan has to be approved by the majority of creditors. Therefore, unique to our paper, we use the financial projections provided in the plan of reorganization to predict re-filings.

To collect the financial projections and valuation data, we downloaded disclosure statements from PACER for the 179 cases that we obtained after excluding 363 Asset Sales (see Table 1). In every case, we downloaded the disclosure statement approved by the court. In some cases, disclosure statements are heavily contested and are often amended before the Chapter 11 plan of reorganization is confirmed. The financial data contained in the disclosure statements presents a few limitations: First, there is no unified format or requirement for financial projections, although in most cases the income and cash flow statement projections for at least three financial years are provided, with balance sheet projections provided less often. Second, companies emerge from bankruptcy throughout the calendar year, and sometimes projections are provided only for the remaining part of the emerging year. Third, in some cases, projections or valuation are not provided or lack essential metrics.

For the 179 companies in our sample, we collected the following data - projections of cash, total assets, and total debt at the end of the year when the company emerged; three-year projections (including a year of emergence) for EBIT, EBITDA, and Interest Expense; and enterprise value. Following the data collection and clean up process mentioned at the beginning of this Chapter, 35 companies were dropped from the sample, resulting in our final sample of 144 companies.

Given the challenges presented by the data obtained from disclosure

Table 2: Variable Definitions

Variable	Definition
Financials	
Debt/EV	Projected Debt in Year of Emergence divided by Enterprise Value
Cash/TA	Projected Cash in Year of Emergence Divided by Total Assets in Year of Emergence
EBIT/TA	If company emerged in the first half of a year: Projected EBIT in the Year of Emergence divided by Total Assets, If company emerged in the second half of a year: Projected EBIT in the Year 1 divided by Total Assets
Interest/EBITDA	Projected Interest expense in Year 1 divided by projected EBITDA in Year 1
EBITDA Growth	If company emerged in the first half of a year: Change in projected EBITDA between Year 1 and Year of Emergence divided by Total Assets, If company emerged in the second half of a year: Change in projected EBITDA between Year 2 and Year 1 divided by Total Assets
Assets	Projected Total Assets in Year of Emergence
Chapter 11 Variables	
Free-Fall	Bankruptcy was not Prepackaged nor Pre-negotiated
Prepackaged	Bankruptcy was prepackaged
Pre-negotiated	Bankruptcy was pre-negotiated
Unsecured Committee	Committee of Unsecured Creditors was appointed
Equity Committee	Equity Committee was appointed
Planned Sale of Assets	Company planned to sell assets in their plan of reorganization
Inexperienced Judge	Judge signing the disposition order had never signed a disposition order on a big bankruptcy case, i.e. case in the LoPucki-BRD, before.
Delaware or NY SD	Bankruptcy was filed in Delaware or the Southern District of New York
Ownership	
Lenders	Senior Lenders without a specialised debt-for-control gained significant control of the company
Activists Investors	Activist investors gained significant control of the company
Private Equity Investors	Private Equity investors gained significant control of the company
Other Control	Other Investors, e.g., strategic investors, gained control of the company, or company remained under private ownership
Economic variables	
GDP Growth FY-2	% Change in GDP from year 2 before bankruptcy to year 1 before bankruptcy
GDP Growth Filing	Growth in GDP between Filling and Emergence date divided by number of years between Filing and Emergence date

Financial variables are taken from disclosure statements. Ownership was sourced from S&P CapIQ and Reuters Eikon. All other variables were sourced from the Lopucki BRD statements, we could not simply use a proven bankruptcy prediction model, i.e. Z-Score, but had to creatively designing our variables. As a result, we constructed five primary variables: (1) *Debt/EV*; (2) *Cash/TA*; (3) *EBIT/TA*;(4) *Interest/EBITDA*; (5) *Assets*, to study the four fundamental factors that had been found to affect bankruptcy rates - capital structure, operational performance, current liquidity, and asset size (Ohlson, 1980). In addition to these five variables, we also wanted to examine if projected growth had any link to recidivism, and so included a variable measuring EBITDA growth. The full definition of the variables chosen for analysis can be found in Table 2.

There are a few points regarding the financial variables we created and the data set challenges we faced that we think are necessary to discuss. Firstly, because balance sheet projections are sometimes omitted, we used ratios that only required balance sheet items that are provided even if projections are missing - cash, total debt, and total assets. Secondly, because companies emerge from bankruptcies in various months of the calendar year, we faced difficulty choosing the projection year most appropriate for our study. For example, for a company that emerges from bankruptcy at the beginning of the year, the projection for the year of emergence will be much more relevant than for a company that emerges at the end of the year. Thus, for *EBIT/TA* and *EBITDA Growth*, we use the year of emergence if the company emerged in the first half of the year, and the first year after emergence if it emerged in the second half. However, for *Interest/EBITDA*, we use the first year after emergence. This is because we want to analyze Interest and EBITDA that are not influenced by the interest expense of previous debt and restructuring charges, respectively. Thirdly, in a few cases when projections for the year of emergence are only available for the remainder of the year, we normalize them for the whole year by assuming such performance was uniformly conducted over the months not included in the financials.

3.5 Summary Statistics

Table 3 reports the key summary statistics on legal and ownership variables from the population for Chapter 11s, Chapter 22s and All cases together. Several patterns emerge from the table.

Firstly, we observed distinct variations in ownership variables between Chapter 11s and Chapter 22s. Activist investors were present in a larger portion of Chapter 11s than Chapter 22s, a trend similarly noted by Hotchkiss and Mooradian (1997). They found activists to have a positive impact on the operational performance of companies after bankruptcy, which may help explain why a larger share of companies that survived presented activist

Table 3: Summary Statistics - Ownership & Court Process

Variable Name	Chapter 22s (%)	Chapter 11s (%)	All (%)
Ownership			
Lenders (base)	52.9%	46.4%	47.9%
Activists Investors	20.6%	33.6%	30.6%
Private Equity Investors	14.7%	6.4%	8.3%
Other Control	11.8%	13.6%	13.2%
Bankruptcy Class			
Free Fall (base)	38.2%	44.5%	43.1%
Prepackaged	23.5%	20.9%	21.5%
Pre-negotiated	38.2%	34.5%	35.4%
Chapter 11 Variables			
Unsecured Committee	70.6%	74.5%	73.6%
Equity Committee*	5.9%	18.2%	15.3%
Planned Sale of Assets	44.1%	36.4%	38.2%
Inexperienced Judge	17.6%	10.0%	11.8%
Delaware or NY SD*	58.8%	80.9%	75.7%
N	23.6% (34)	76.4% (110)	100% (144)

Source: Authors' Sample and Computations.
Note: Statistics refer to the initial bankruptcy.
* Difference between means of C11s and C22s is significant at 0.05 level.

ownership compared to those that went bankrupt. It may also be the case that this is a matter of self-selection, given that activist investors would simple 'self-select' to own better companies, with lower probabilities of default. In the same line of logic, PE investors likely also self select companies with lower probabilities of default, particularly when compared to senior lenders. This view was informed by the work of Kai and Prabhala (2007) on self-selection models in corporate finance. Lenders were more prevalent as owners in Chapter 22 companies, but constituted nearly half of all ownership in the population. As this area of research remains understudied, one cannot assume any causative impact of lender-ownership on companies. However, as detailed by K. M. Ayotte and Morrison (2009), senior lenders likely obtain control as a consequence of the stringent covenants in place and their secured position, rather than having an investment approach that covets ownership and operational improvement as is the case for Activists. 'Other Control' had limited deviations between the two groups, and this may be explained by how strategic investors invest and operate differently to other stakeholders. Additionally, while some of these companies continued under private ownership, given the category encompasses different ownership cases it is hard to develop a coherent hypothesis for it. Private Equity investors constituted a minority share in both sample groups, but constituted a materially higher proportion of the Chapter 22 group than the Chapter 11 group. This trend is also noted by Hotchkiss et al. (2021), where they observed that PE-backed firms had higher leverage and defaulted at higher rates than non-PE backed firms. This was also further confirmed by Tykvová and Borell (2012). There may be some unobserved effects of excess leverage leading to this result, and this paper will further address the topic in Chapter 5 by examining the significance of this variable.

This paper also reviewed the Chapter 11 approach utilised by the sample of debtors. We classify the approach as either free fall, prepackaged or pre-negotiated (see Table 2 for definitions). For a more in-depth review of bankruptcy classification, please refer to LoPucki and Doherty (2015). In this paper, we follow the work of Chatterjee et al. (1996) whereby we perceive free-fall bankruptcies as those which allow the most capital structure transformation, due to the numerous creditor and equity committees that negotiate against impairment (often times arguing for equity in place of debt). Pre-packaged and pre-negotiated bankruptcies occupy the other end of the spectrum with respect to capital restructuring, usually offering 'amend and extend' options for debt rather than debt write downs. This can be explained by the requirement for unanimous approval to arrange a prepackaged bankruptcy, or approval from at-least a major creditor in the case of a pre-negotiated bankruptcy, making significant debt reduction harder to achieve. This lack of leverage reduction would theoretically lead to a higher likelihood of default as per K. M. Ayotte and Morrison (2009), and this is encouragingly observed within our data set. Free Fall's constitute the largest bankruptcy class among Chapter 11s, with both the prepackaged and pre-negotiated classes representing a smaller proportion compared to their share among Chapter 22s.

Some further legal variables are also studied, covering the presence of unsecured creditor and equity committees, sale of assets, experience of judges and the location of the court (a review on forum shopping is provided by Parikh (2013)). We found it important to cover these variables, as the legal process was shown to have a significant impact on the outcomes of bankruptcy processes in a study by LoPucki and Doherty (2015). Our study of equity and unsecured creditor committees found that while unsecured creditors were similarly represented in both groups, equity committees were more prevalent among Chapter 11s. This trend may be explained by the fact that companies with lower levels of impairment/financial distress can provide more recovery to equity investors than those in the Chapter 22 group, implying that a greater presence of equity committees is a signal of a less distressed debtor (K. M. Ayotte & Morrison, 2009). Furthermore, in our sample, judge inexperience is shown to have a higher presence in Chapter 22 cases. We classified judge experience as whether the judge presiding over the case had experience with at least 1 major bankruptcy case. This trend was also seen in the main study carried out by LoPucki and Doherty (2015), where a potentially causative link was drawn between judge experience and bankruptcy outcomes. We lastly studied the prevalence of forum shopping, i.e. the choice of court to apply for Chapter 11. In the literature, there is coverage on why the Delaware or Southern District of New York courts are favourable to companies, due to their highly experienced judges, creditor and management friendly practices, and quick processing times, with evidence provided by LoPucki and Doherty (2002). This is especially relevant in the case of pre-negotiated or prepackaged bankruptcies, in which the debtor prioritises the speed of Chapter 11 execution. This trend is similarly observed in our data set, whereby Delaware and New York courts compose the vast proportion (81%) of Chapter 11s, but only 59% of Chapter 22s. This deviation may be explained by the need for more thorough restructuring among Chapter 22s, as evidenced in Eisenberg and LoPucki (1998). The prevalence of Delaware and the Southern District of New York among Chapter 11s presents an interesting observation, as prior literature by scholars such as LoPucki (2005) presented opposing views on the efficacy of these courts.

Table 3 presents summary statistics of financial and economic variables grouped by recidivism status. The average size of our sample firms, measured by total assets (*Assets*), is $2586 million in 2022 current dollars, putting the typical sample firm between the 7th and 6th decile of the LoPucki BRD universe. While Chapter 11s are bigger than Chapter 22s on average - $2897 million vs. $1581 million, their median is smaller than the median of Chapter 11s - $614 million vs. $1072 million. This suggests that the population of Chapter 11s is disproportionately represented by firms that emerge with assets on the tail-ends of the distribution. When compared to the whole LoPucki BRD population, we found that Chapter 22 cases were smaller, with the average Chapter 22 case occupying the 5th decile of the LoPucki BRD, while Chapter 11s occupied the 7th and 8th decile. Other key deviations between the groups included (1) Leverage, where Chapter 22 companies had *Debt/EV* at 75% on average, compared to 50% among Chapter 11s; (2) *EBITDA/Interest*, where interest coverage ratios were nearly twice as high for Chapter 11 companies as for Chapter 22s. Some measures shows similar trends across both groups, including *EBIT/TA*, *Cash/TA*, management forecasts of *EBITDA growth*. Of these 'similar' ratios, we are most interested in the impact of *EBIT/TA*, which describes a firm's ability to generate returns on its assets. With regards to economic variables the summary statistics show that *GDP Growth FY-2* was on average 2.4% for Chapter 22s whereas for Chapter 11s it was only 1.4% which is a sizeable difference. This suggests that that macroeconomic conditions before bankruptcy are important for recidivism rates. On the other hand, there was little difference in *GDP Growth Filing* between Chapter 11s and Chapter 22s. In Chapter 5, we report the pairwise correlation coefficients among key firm/case characteristics and legal process variables.

Table 4: Summary Statistics - Financial & Economic Variables

Statistic	Median	Mean	St. Dev.	Min	Max
Chapter 22s (N = 34)					
Debt/EV***	0.733	0.743	0.206	0.218	1.207
Cash/TA*	0.034	0.042	0.041	0.001	0.216
EBIT/TA	0.033	0.025	0.096	−0.330	0.168
Interest/EBITDA*	0.465	0.625	0.797	0.133	4.839
EBITDA Growth	0.023	0.037	0.045	−0.024	0.216
Assets	1,072.808	1,580.686	1,400.538	114.012	5,599.544
GDP Growth FY-2**	0.024	0.024	0.011	0.001	0.044
GDP Growth Filing	0.011	0.015	0.019	−0.034	0.063
Chapter 11s (N = 110)					
Debt/EV***	0.508	0.504	0.229	0.000	0.908
Cash/TA*	0.046	0.068	0.073	0.000	0.413
EBIT/TA	0.050	0.041	0.122	−0.565	0.569
Interest/EBITDA*	0.337	0.336	0.201	0.000	1.143
EBITDA Growth	0.023	0.044	0.119	−0.106	1.000
Assets	614.092	2,897.473	7,076.613	30.492	37,289.73
GDP Growth FY-2**	0.017	0.014	0.021	−0.040	0.044
GDP Growth Filing	0.013	0.016	0.018	−0.033	0.116
All (N = 144)					
Debt/EV***	0.590	0.561	0.246	0.000	1.207
Cash/TA*	0.043	0.062	0.068	0.000	0.413
EBIT/TA	0.046	0.037	0.116	−0.565	0.569
Interest/EBITDA*	0.356	0.404	0.439	0.000	4.839
EBITDA Growth	0.023	0.043	0.106	−0.106	1.000
Assets	698.756	2,586.565	6,240.133	30.492	37,289.73
GDP Growth FY-2**	0.017	0.017	0.020	−0.040	0.044
GDP Growth Filing	0.013	0.016	0.018	−0.034	0.116

Source: Authors' Sample and Computations.
Note: Statistics refer to the initial bankruptcy.
*, **, *** Difference between means of C11s and C22s is significant at 0.05, 0.01, 0.001 level.

In summary, Table 2 & 3 suggest that companies which avoid recidivism emerge from their initial Chapter 11s with lower leverage and higher liquidity than those that re-filed, highlighting the importance of efficient capital structure reconstruction and debt reduction. Companies which find themselves owned by activists during Chapter 11 are observed to have lower recidivism rates, while those under private equity control face a higher risk of recidivism. Furthermore, Chapter 11s have a tendency to proceed with free-fall bankruptcy, due to the options it provides vis-à-vis debt reduction. Additionally, cases where equity committees are present tend to have lower recidivism rates, while those where asset sales are planned have a higher rate of recidivism. The inexperience of judges and the selection of courts is also observed to have variation between the two groups studied, with the Chapter 11 group having more experienced judges presiding over the bankruptcy process, in more renowned bankruptcy courts. In Chapter 5, we examine the persistence of these patterns in multivariate regressions that control for financial, legal, economic, and stakeholder characteristics.

4 Methodology

In our paper, we use a logistic regression model to estimate the probability of recidivism, i.e., a company emerging from bankruptcy subsequently re-files within five years. The logistic regression model is optimal for studies like ours, where the outcome is binary (i.e. re-file & not re-file). Furthermore, the logistic regression model has a few advantages that makes it a popular choice in bankruptcy literature (see for instance Ohlson (1980)). It has relatively few restrictive assumptions, supports all variable types, and is relatively transparent as its results are probabilities between zero and one. In this section, we discuss the definition of the model, assumptions of the model and their testing, and how the logit model is used for predicting recidivism.

4.1 Logistic Regression Model

The logistic regression model for binary categorical variable y and k independent variables $x_1, x_2, \ldots, x_k$ is defined as (based on Menard (2002) and Wooldridge (2012)):

$$logit(y) = log\left(\frac{P(y=1)}{1-P(y=1)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 x_2 + \cdots + \beta_k x_k \tag{1}$$

where β_0 is the intercept and $\beta_1, \beta_2, \ldots, \beta_k$ represents the parameters of the model. Alternatively, the model can be rewritten as:

$$P(y=1) = \frac{e^{(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k)}}{1+e^{(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_k x_k)}} \tag{2}$$

The model is estimated using maximum likelihood estimation, which maximizes the log-likelihood given by:

$$l = \sum_{n=1}^{N} y_n log(P(\boldsymbol{X_n})) + \sum_{n=1}^{N}(1-y_n)log(1-P(\boldsymbol{X_n})) \tag{3}$$

where n is the n-th observation and $\boldsymbol{X_n}$ is the vector of the independent variables for the n-th observation.

4.2 Model Assumptions

Compared to other commonly used statistical tools, the logistic regression model has comparatively few assumptions. We present the results of assumption testing in Appendix A. For a more comprehensive review of key assumptions of the logistic regression model, please see Menard (2002).

4.2.1 No Strongly Influential Outliers

The logistic regression model is sensitive to highly influential outliers that can diminish the statistical power and distort the accuracy of the model. To find highly influential data points, we calculate the Cook's Distance, which measures the change in the regression model when the given data point is removed (Cook & Weisberg, 1982). Regarding Cook's distance threshold, we deem a data point to be influential when the Cook's Distance is higher than $4/N$ (where N is the number of data points). We then look at influential data points to see if they are also outliers which we define as having an absolute standardized residual value higher than 3.

4.2.2 Absence of Collinearity

Collinearity arises when independent variables are correlated with each other. Although higher collinearity does not result in biased and inefficient estimators, it increases standard errors and thus reduces the overall significance of the model. To deal with this issue, we calculate a variance inflation factor (VIF) that measures the degree of collinearity present. As a rule of thumb, a VIF higher than 5 indicates problematic collinearity. Complementing our VIF calculation, we also use correlation matrices.

4.2.3 Linear Relation Between Continuous Variables and Logit of the Outcome

The logistic regression model assumes that the relationship between continuous variables and the logit of the dependent variable Y is linear, i.e., that change in *logit(Y)* is constant for any value of X. Commonly this assumption is tested using Box-Tidwell transformation. However, this transformation works only if continuous variables are strictly positive, which is rarely the case among financial ratios. Therefore in our case, we utilize scatter plots to check linearity visually as recommended by Menard (2002).

4.3 Making Predictions

4.3.1 Fundamentals

By definition, the logistic regression model estimates the probability of recidivism for every company in the sample in the range of zero to one. To classify a company as Chapter 11 or Chapter 22, a probability cut-off point needs to be selected. For example, when we set the cut-off point at 0.5 probability, we classify every company with an estimated probability of refiling higher or equal to 0.5 as Chapter 22 and every company with an estimated probability of refiling lower than 0.5 as Chapter 11. In doing so, we classify some companies correctly and some incorrectly. We speak of a type I error when a Chapter 11 company is classified as a Chapter 22 and a type II error when a Chapter 22 company is classified as a Chapter 11.

In practice, there is no reason why the cut-off point should be set to 0.5. The selection depends on the cost of type I and type II errors, i.e., the cost of misclassifying Chapter 11s and misclassifying Chapter 22s. These costs depend on the model's concrete application and the goals of the party applying the model.

4.3.2 Evaluation of Predictive Performance

Assessing the predictive performance of the bankruptcy prediction model is a complex topic that lacks a clear consensus. In practice, various goodness-of-fit measures are utilized, with the most common being either the lowest sum of type I and type II errors or maximum percentage of correct classification (Balcaen & Ooghe, 2006). The choice of goodness-of-fit measure inherently depends on the cost of type I errors. In our paper, we make no assumption about the costs of type I and type II errors and treat their cost equally. As a reason we use the maximum percentage of correct classification, which we refer to as *Max Classified* in the paper, as our goodness of fit measure. As a complementary measure of goodness of fit, we use McFadden's Pseudo Adjusted R^2, which similarly to OLS Adjusted R^2, penalises addition of new variables. McFadden's Pseudo Adjusted R^2 is defined as:

$$R^2_{adj} = 1 - \frac{log(L_c) - K}{log(L_{null})} \tag{4}$$

where L_c is the likelihood value of current model, L_{null} is likelihood value for null model and K is the number of additional parameters relative to the null model.

4.3.3 Stability of the Model

A common issue in bankruptcy prediction is that models became unstable and lose their predictive power when used on the new data (Balcaen & Ooghe, 2006). This tends to happen both as a result of over-fitting models and pooling data across time which requires stable relationships between independent and dependent variables. In general, over-fitting stems from a lack of clear consensus on financial ratios for bankruptcy prediction. The lack of consensus then often results in choosing from a myriad of financial ratios to fit the given sample best.

One method to check the stability of the model is to conduct split-sample testing. In split-sample testing, the data set is split into a training and a testing sample. The model is then estimated on the training sample, and the collected estimated coefficients and cut-off point are then used to predict the outcomes on the testing sample.

In our study, we wish to check how older cases predict newer cases, as forecasting serves as the primary purpose of our model. Therefore we order the sample by bankruptcy filing date and use the oldest 60% of our sample as the training sample, and the remaining 40% as the testing sample.

5 Regression Analysis

To analyse the key determinants of bankruptcy recidivism, we developed and ran regression models that related the occurrence of re-filing to certain firm and case characteristics. Utilising a dependent binary variable '*Re-Filed 5Y*' we built a model explaining bankruptcy recidivism within a 5 year period. We employed a logit-regression model following its favorable properties and extensive usage in bankruptcy literature (e.g. Ohlson (1980), Hotchkiss and Mooradian (1997), Jiang et al. (2012)), studying the effects of financial, legal and ownership variables on bankruptcy recidivism, as similarly conducted by Altman (2014), with the distinction being their sole focus on corporate liquidity, solvency, profitability and leverage.

Given the large number of variables available and the risk of over-specification, we wanted to only include the most important variables. We began our study by regressing *Re-Filed 5Y* on all variables in our summary statistics table except for base groups of dummy variables. The base group for ownership is set as *Lenders*, and for bankruptcy approach as *Free-Fall*. Based on this initial regression, we selected a collection of variables that we analyzed further by creating five specifications of the final model.

5.1 Initial Analysis

Table 5 presents the results from our initial regression. Our testing appears to show that within financial determinants, *Debt/EV* and *EBIT/TA* have the most significant impact, while other previously interesting variables remain insignificant. With regard to the legal, ownership and economic variables, the existence of an equity committee, the experience of the judge involved, the ownership of an activist investor and the economic growth prior to bankruptcy were shown to carry some significance.

To address the over-fitting of the initial model we act to further reduce the number of variables studied, utilising results from Table 5 alongside the summary statistics for each group. We attempted to exclude any variables that were shown to lack significance at the 10% level, or those with weak theoretical explanatory power that presented similar observations within the Chapter 22 and Chapter 11 groups. Furthermore, we deal with the issue of non-linear relationships between continuous independent variables and the logit of the dependent variable. In Section 3.5, we noticed that the non-refiling population is composed both of firms emerging with the most, and the least, assets, suggesting a non-linear relationship. We account for this by including a logarithm of assets (*log (Assets)*).

Eventually, we arrived at a final list of 11 explanatory variables which we believed had the potential to explain the incidence of bankruptcy recidivism in a generalizable form. These were: (i) *Debt/EV*; (ii) *Cash/TA*; (iii) *EBIT/TA*; (iv) *Assets*; (v) *log (Assets)*; (vi) *GDP Growth FY-2*; (vii) *Activist Investors*; (viii) *Private Equity Investors*; (ix) *Other Control*; (x) *Inexperienced Judge*; and (xi) *Equity Committee.* Observe that the variables (i) - (vi) are continuous while variables (vii) - (xi) are binary. For definitions, please refer to Table 2.

Table 5: Regression Table With All Variables

	Dependent variable:
	Re-Filed 5Y
Financial Variables	
Debt/EV	5.864*** (1.622)
Cash/TA	−8.608 (5.954)
EBIT/TA	−6.812* (3.263)
Interest/EBITDA	1.507 (1.238)
EBITDA Growth	−4.851 (7.559)
Assets	−0.0001 (0.0001)
Chapter 11 Variables	
Prepackaged	−1.554 (1.141)
Pre-negotiated	0.394 (0.666)
Unsecured Committee	−1.192 (0.954)
Equity Committee	−2.445+ (1.293)
Planned Sale of Assets	0.671 (0.612)
Inexperienced Judge	1.717+ (0.993)
Delaware or NYSD	−0.188 (0.717)
Owners	
Activists Investors	−1.170+ (0.730)
Private Equity Investors	0.471 (1.012)
Other Control	−0.642 (0.856)
Economic Variables	
GDP Growth FY-2	32.741+ (17.508)
GDP Growth Filing	4.511 (11.657)
Intercept	−3.648* (1.528)
Observations	144
Note:	+p<0.1; *p<0.05; **p<0.01; ***p<0.001

5.2 Model Specification & Discussion

Based on the final collection of variables in the previous section, we created five specifications of the logistic regression model, which we present in Table 6. We also provide the correlation matrix for all the variables used in Table 8, which shows an overall low correlation among predictors. Financial and Size variables (Specification (1)) acts as the 'base' for our model. We examine the changes in the model's predictive ability when other variables are supplemented, discussing the predicted effects of these variables. Specification (1) utilises only financial ratios and size variables. In Specification (2), we include *GDP Growth FY-2* to control for the effect of different economic environments prior to the initial bankruptcy filing, and to implicitly control for time in the data set. In specification (3), we include 3 binary variables in our regression, controlling for the type of owner. With Specification (4), while utilising the same base, we add legal variables. Finally, Specification (5) includes all variables, to provide a highly controlled comparison specification, not withstanding its over-fitted nature.

5.2.1 Financial Variables & Effects

As is the case in general bankruptcy literature (Altman (1968), Ohlson (1980)), financial and asset size variables also play a crucial role in predicting bankruptcy recidivism. Specification (1), utilising just financial and size variables, classified 84.7% of companies correctly with an Adjusted Pseudo R2 of 19%. In accordance with expectations, the estimated coefficients suggest that higher leverage (*DEBT/EV*) increases the likelihood of recidivism, whereas higher liquidity (*Cash/TA*) and operational performance (*EBIT/TA*) reduce the likelihood of recidivism. Clearly, the *DEBT/EV* is by far the most significant variable, significant even at 0.001 level. *Cash/TA* and *EBIT/TA* fall short of being significant at 0.05 level. We hypothesise that their lack of significance might be caused by the low reliability of the financial projections, a theory supported by Michel et al. (1998). It is possible that since debt levels are relatively easy to predict and enterprise value cannot be completely fabricated (as it is heavily contested in bankruptcy proceedings), *Debt/EV* is less affected by unreliable predictions. When assessing the importance of *DEBT/EV* (and other variables used in logistic regression), it is necessary to not only look at the estimated coefficients but also at distribution, i.e. mean and standard deviation, as presented in Table 4. Given its estimated coefficient of 5.58, mean of 0.56, standard deviation of 0.25, and non-uniform presence in the population groups, *DEBT/EV* is evidently the most important factor in determining the probability of recidivism. Using a similar

Table 6: Final Specification

	Dependent variable:				
	Re-Filed 5Y				
	(1)	(2)	(3)	(4)	(5)
Debt/EV	5.582***	5.542***	5.681***	5.591***	5.557***
	(1.302)	(1.321)	(1.367)	(1.357)	(1.399)
Cash/TA	-8.796+	-7.539	-8.481+	-6.943	-8.548
	(4.657)	(4.800)	(4.998)	(4.988)	(5.278)
EBIT/TA	-5.201+	-5.654+	-5.977+	-5.784+	-5.688+
	(2.716)	(2.956)	(3.121)	(3.193)	(3.364)
Assets	-0.0002	-0.0002	-0.0003+	-0.0003	-0.0003+
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
log(Assets)	0.639+	0.779*	0.829*	1.052*	1.109*
	(0.348)	(0.367)	(0.385)	(0.416)	(0.431)
GDP Growth FY-2		36.191*	33.186*	41.814*	38.320*
		(15.743)	(15.490)	(17.041)	(16.861)
Activists Investors			-0.643		-1.046
			(0.610)		(0.685)
Private Equity Investors			1.175		0.692
			(0.886)		(0.946)
Other Control			-0.318		-0.540
			(0.740)		(0.801)
Inexperienced Judge				1.616+	1.794+
				(0.863)	(0.926)
Equity Committee				-1.919+	-2.056+
				(1.038)	(1.137)
Constant	-7.979***	-9.590***	-9.730***	-11.59***	-11.49***
	(2.402)	(2.621)	(2.777)	(2.974)	(3.026)
Max Classified	84.7 %	86.8 %	87.5 %	87.5 %	88.9 %
Percentage Chapter 11s	76.4 %	76.4 %	76.4 %	76.4 %	76.4 %
Cut Off	0.49	0.47	0.52	0.47	0.44
Type I Error	6.4 %	4.5 %	3.6 %	3.6 %	6.4 %
Type II Error	44.1 %	41.2 %	41.2 %	41.2 %	26.5 %
Adjusted Pseudo-R2	19.0 %	22.0 %	20.7 %	24.3 %	23.1 %
Observations	144	144	144	144	144
Note:		+p<0.1; *p<0.05; **p<0.01; ***p<0.001			

strand of logic, *EBIT/TA* and *CASH/TA* are observed as being of lesser importance. With respect to the impact of these variables, Altman (2014)'s observation that his sample was greatly impacted by leverage, and a similar observation by LoPucki and Whitford (1992), where it was observed that both leverage and operational issues were cited as the primary reason for a Chapter 22 filing, give some credence to the notion.

5.2.2 Assessing Asset Size

Assets in our specifications are represented by two variables *Assets* and *log(Assets)*. Their estimated coefficients represent a phenomenon we have discussed in Section 3.5 - companies emerging with very high or very low assets (given our sample values) are less represented among the refiling companies. On average, however, the asset size of the Chapter 22s is lower than that of Chapter 11s. We hypothesize that there are certain 'size' advantages during the bankruptcy and post bankruptcy period that favours companies with large asset size. This may be due to a lower cost of capital (Van Dijk, 2011) and larger firms having better access to public equity financing, which Brav (2009) argue is less costly than private equity financing. Additionally, larger assets can be sold more efficiently prior to bankruptcy, especially if separated from the main company; we hypothesize that this provides larger entities with more sources of liquidity in the event of financial distress.

On the other end of the spectrum, the firms with very low assets in our sample are those that have significantly reduced their assets size. Denis and Rodgers (2007) found that companies that reduce their asset size are more likely to have positive operating performance and have a lower likelihood of recidivism, which our results support.

5.2.3 Pre-Bankruptcy GDP Growth

The addition of *GDP Growth FY-2* in Specification (2) further increases predictive performance to 86.8% and also improves the fit of the model. The *GDP Growth FY-2* is significant at 0.05 level and has a relatively strong effect on the probability of refiling given the high estimated coefficient of 36.19, mean of 0.02 and standard deviation of 0.02. We use *GDP Growth FY-2* as a control for the economic environment prior to initial bankruptcy. This is important as we pool data across time. The direction of the coefficient suggests that companies that file for Chapter 11 bankruptcy after a period of high growth fare worse than those that file for Chapter 11 bankruptcy after a period of low growth or decline.

One logical explanation is that there is a difference between the proportion of economically and financially distressed firms going bankrupt during periods of high GDP and low GDP growth. Specifically, there would be a higher proportion of firms filing for bankruptcy because they are not viable as a going concern after periods of low growth than after high growth. This could have a large influence on recidivism rates as Tashjian (2017) found that firms that are economically distressed re-file more often than financially distressed firms. We hypothesize that firms filing for Chapter 11 in good macroeconomic environments likely suffer from unsustainable business models rather than oppressive markets, thus making it easier to identify recidivists in times of good GDP growth.

5.2.4 Private Equity, Activist & Other Control

The nature of a debtor's claims, and the identity of the owners of those claims, have an important effect on the dynamics of the renegotiation process. In many larger cases in our sample, original bank lenders have sold their positions to specialized investors as the firm's performance notably declines. Similarly, private-equity-like investors may have replaced original purchasers of the firm's bonds or notes, or even claims of trade creditors. Including ownership variables in Specification (3), in order to address these effects, only marginally increases the classification performance while reducing fit as measured by the Adjusted Pseudo R2. All the ownership variables are insignificant at the 0.05 level, and therefore, we cannot draw any strong conclusions about the effects of ownership on recidivism. In general, the effects of ownership appear to be rather small, indicating that companies controlled by activists fare better than companies controlled by lenders. This must be considered alongside the usage of senior lender as the base control group. Senior lenders, when abruptly placed into ownership of a company, fare worse than Activists. This may be as Activist investors, including those with a specific debt for control strategy, intend to acquire debt with an aim to take control and improve an asset.

However, lenders in control primarily aim to sell the company (as suggested by K. M. Ayotte and Morrison (2009)), or perform many iterations of a fire sale, while also lacking the experience needed to create value.

On the other hand, companies controlled by private equity seem to fare worse than those controlled by lenders. We hypothesize that PE investors decrease the cost of financial distress but increase the risk involved due to higher leverage as part of the LBO, as evidenced by Hotchkiss et al. (2021). The additional leverage carried by firms post-buyout, alongside the margin expansion sought by investors, adds undue pressure to portfolio companies, eventually leading to financial distress. However, evidence to the contrary is presented in Hotchkiss et al. (2021), with the conclusion stating that PE investors may have a value-creating impact. Another contradictory finding is that PE-backed firms in distress often restructure out-of-court, or through pre-packaged bankruptcy agreements; recent data from Hotchkiss et al. (2021) illustrated that c.1/2 of the PE-backed restructurings studies were held out-of-court, as opposed to only 1/3 of non-PE-backed firms (the majority restructure via "free-fall" Chapter 11s). This is also seen in the work of Cohn et al. (2022), which addresses the value creating aspect of PE LBOs.

Table 7: Characteristics of companies by owners (Means)

Variable Name	Lender	Activist	PE	Other
Debt/EV	0.558	0.536	0.597	0.602
Cash/TA	0.064	0.048	0.063	0.086
EBIT/TA	0.040	0.047	0.049	0.000
Assets	2659	1784	6568	1669
log(Assets)	6.86	6.54	7.38	6.54
GDP Growth FY-2	0.017	0.016	0.023	0.013
Equity Committee	13.0%	13.6%	25.0%	21.1%
Inexperienced Judge	5.8%	18.2%	16.7%	15.8%

Source: Authors' Sample and Computations

To better understand the role of owners in bankruptcies, we also examined how predictors differ amongst the various classes of owners, which we have summarised in Table 7. Several interesting patterns emerged. Firstly, private equity investors tend to engage in much larger cases, with a mean asset size of $6568 mil. Secondly, PE funds tend to be disproportionately present in cases where equity committees were established, giving more support to the hypothesis that PE investors add value to firms in distress. Lastly, activists, PE, and other owners seem to be more involved in cases where the presiding judge lacks experience. We hypothesize that these investors might be able to influence the court process when the judge is inexperienced.

5.2.5 Controlling for Legal Variables

Adding two legal variables in Specification (4) also only marginally increases predictive power to 87.5%, but unlike the ownership variables also increases fit. Both variables *Inexperienced Judge* and *Equity Committee* fall short of being significant at the 0.05 level, possibly because both situations are quite rare. On the other hand, the effects of these two variables are relatively strong. The coefficient of *Equity Committee* hints that when an equity committee is established, refiling is less likely. It is to be expected that equity committees will be over-represented in Chapter 11 companies (as we discussed in section 3.5) because an equity committee is only established when equity holders successfully argue that the value of the company is higher than the value of more senior claims. The estimate of *Inexperienced Judge* effect is distinctly positive, suggesting that the likelihood of refiling increases when the presiding judge lacks experience with a major bankruptcy case.

5.2.6 Final Specification Choice & Trade-offs

For completeness, we also provide Specification (5) with all variables. Combining ownership and legal variables increases prediction power further to 88.9% with a slightly lower Pseudo Adjusted R2 than Specification (4), but better than Specification (2). The change in estimated coefficients of *Activist Investors* and *Private Equity Investors* results from those investors being over-represented in cases led by judges without experience in a major case.

Though Specification (5) of our model correctly classifies the highest percentage of companies, it is likely not a good candidate for a distress predictor model. Unfortunately, bankruptcy prediction models tend to suffer from over-fitting and the subsequent loss of predictive power when used on new data, as we discuss in Section 4.3.3. It seemed prudent to trade a few percentage points of predictive performance for a lower count of variables and more stability. Therefore, Specification (2) or (4) stood out as more reasonable choices for a potential distress predictor model. Our final predictor utilised Specification (2), which we discuss in detail in Section 6.

Lastly, we comment on assumption testing based on section 4.2 provided in Appendix A. While we test the assumptions for all specifications, we only provide and comment on the results of assumption testing for Specification (2). Regarding influential outliers (summarised in Table 10), we found 7 data points that were influential with respect to Cook's distance. However, only one of these points was an outlier based on the standard residual value threshold. Given the limited number of influential outliers, we decided no special treatment of outliers was necessary. Multicollinearity is not an apparent problem in our study, with very low values of VIF recorded in Table 11; the correlation matrix presented in Table 8 shows that the only noteworthy correlation is between *Cash/TA* and *EBIT/TA*, and naturally *Assets* and *Log(Assets)*. Lastly, the linear relationship between continuous variables and log-odds was tested visually using scatter plots. The non-linearity in *Assets* was treated by including *Log(Assets)*, as was already mentioned. For the other variables, we concluded that transformation was not needed.

Table 8: Correlation Matrix

	Debt/ EV	Cash/ TA	EBIT/ TA	Assets	$l_A ssets$	g_GDP FY-2	Activist Inv.	PE Inv.	Other Own.	Inexp. Judge	Eq. Comm
Debt/EV	1	-	+	+	+	+	-	+	+	-	-
Cash/TA		1	-0.43	+	+	-	-	+	+	-	+
EBIT/TA			1	-	+	+	+	+	-	+	+
Assets				1	0.72	+	-	+	-	-	+
$l_A ssets$					1	+	-	+	-	-0.22	+
g_GDP FY-2						1	-	+	-	+	+
Activist Inv.							1	-	-0.26	+	-
PE Inv.								1	-	+	+
Other Own.									1	+	+
Inexp. Judge										1	+
Eq. Comm											1

Note: Correlation table is based on the (5) specification of table 6.If absolute value of correlation coefficient is less than 0.2 then "+" is shown if the coefficient is positive and "-" if it is negative

6 Predicting Recidivism

One of the key goals of our paper is to develop a distressed predictor model (DPM) for predicting bankruptcy recidivism of companies that emerge from Chapter 11 bankruptcy. In this section, we discuss the model, its predictive power and stability, and the potential application of our findings.

6.1 Distress Predictor Model

After careful consideration, we decided to select the second specification of the model presented in Table 6 as the proposed DPM. For clarity, we also

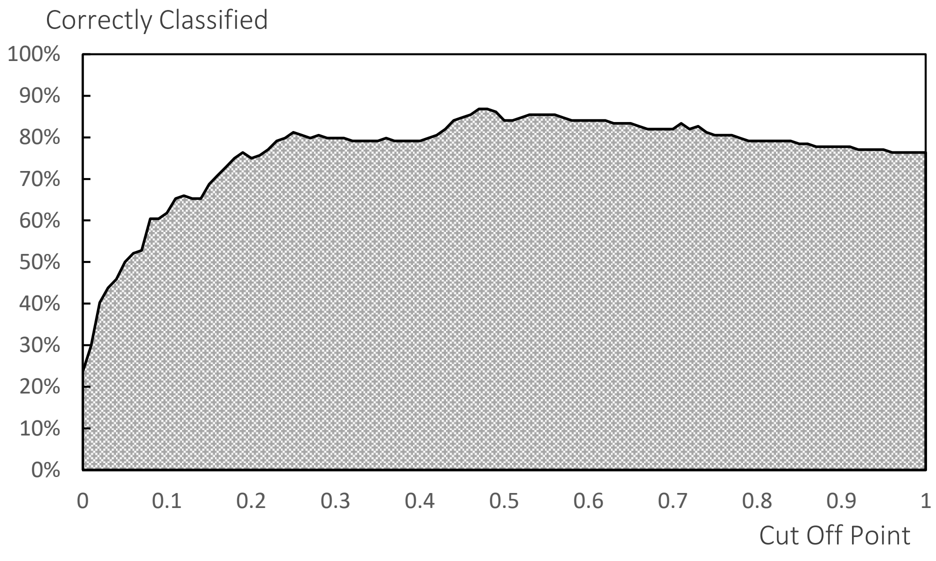
Table 9: Proposed Distressed Predictor Model

	Dependent variable:
	Re-Filed 5Y
Debt/EV	5.542^{***}
	(1.321)
Cash/TA	-7.539
	(4.800)
EBIT/TA	-5.654^{+}
	(2.956)
Assets	-0.0002
	(0.0002)
log(Assets)	0.779^{*}
	(0.367)
GDP Growth Before	36.191^{*}
	(15.743)
Intercept	-9.280^{***}
	(2.488)
Max Classified	86.8%
Percentage Chapter 11s	76.4%
Cut-Off	0.47
Type I Error	4.5%
Type II Error	41.2%
Adjusted Pseudo-R2	22.0%
Observations	144
Note:	+p<0.1; *p<0.05; **p<0.01; ***p<0.001

present it here in Table 9. We chose this specification as it contained all the financial measures that have been shown to have an effect in general bankruptcy literature - capital structure, operational performance, current liquidity, and asset size. Apart from these financial variables, we use *GDP Growth Before* which distinguishes between companies that went bankrupt in periods of strong economic growth and those that went bankrupt in periods of macroeconomic weakness. We also considered including bankruptcy process variables, i.e., *Inexperienced Judge* and *Equity Committee*, that appeared to perform very well in the fifth specification of the model (Table 6). However, given our limited sample size, we decided against it as a larger number of variables could dramatically lower model stability (i.e., predictive power) when used on future data. Moreover, *Equity committees* and *Inexperienced Judges* are rarer to observe at present than in former decades.

Our DPM was able to classify 86.8% of companies correctly given the cut-off point of 0.47, which is a considerable improvement from the baseline prediction of 76.4% that we would have achieve had we assumed that no company re-files. We present the relationship between the percentage of correctly classified companies and the selected cut-off point in Figure 2. Furthermore,

Figure 2: Percentage of Correctly Classified Companies by Cut Off Point



looking at the distribution of Type I and Type II error frequency, the DPM classifies more than half of Chapter 22s correctly - 58.8% (20/34), while misclassifying only 4.5% (5/110) of Chapter 11s. To give a graphical overview of the results, we present the distribution of estimated probabilities for Chapter

11s in Figure 3, and for Chapter 22s in Figure 4. Naturally, the distribution of estimated probabilities is reflected in a frequency of Type I and Type II errors by the cut-off point presented in Figure 5.

Figure 3: Estimated Probability of Recidivism: Chapter 11s

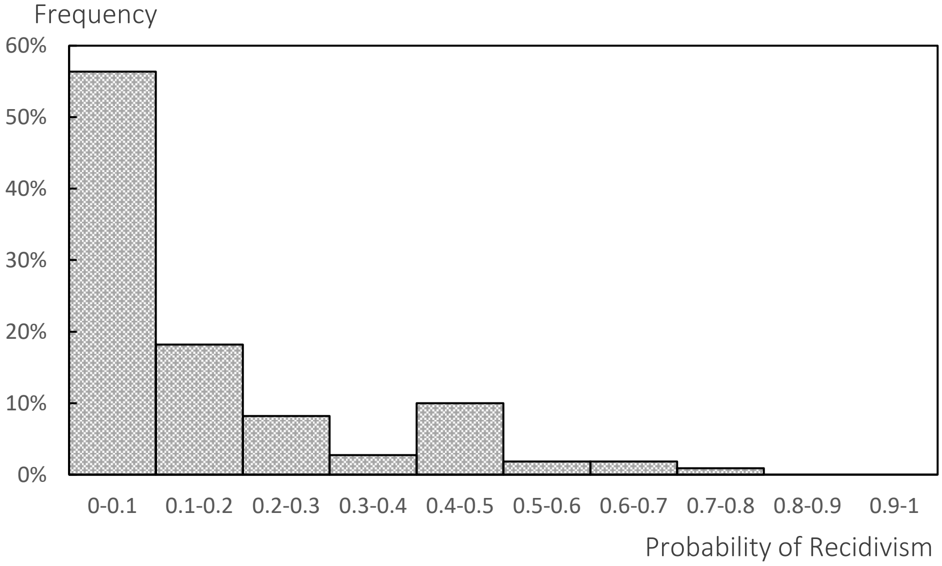


Figure 4: Estimated Probability of Recidivism: Chapter 22s

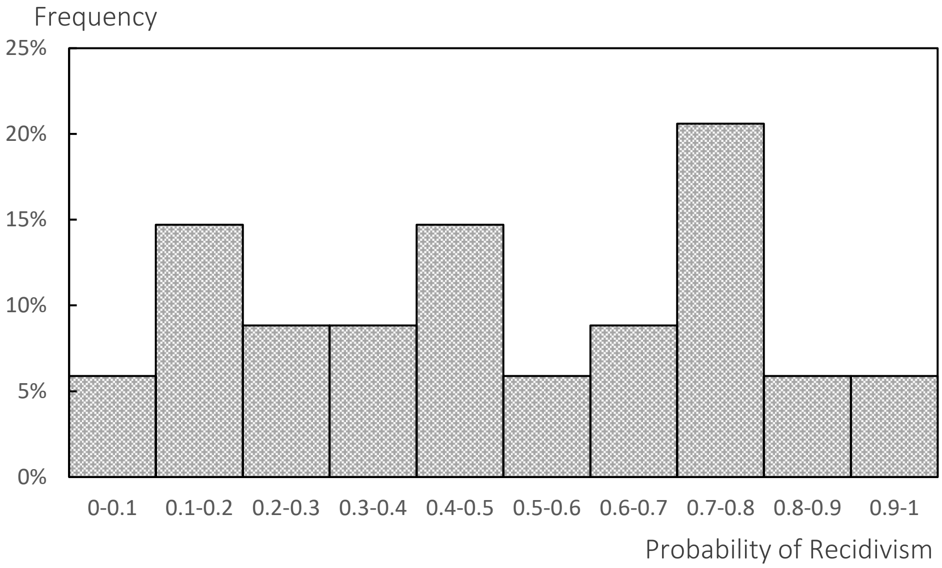
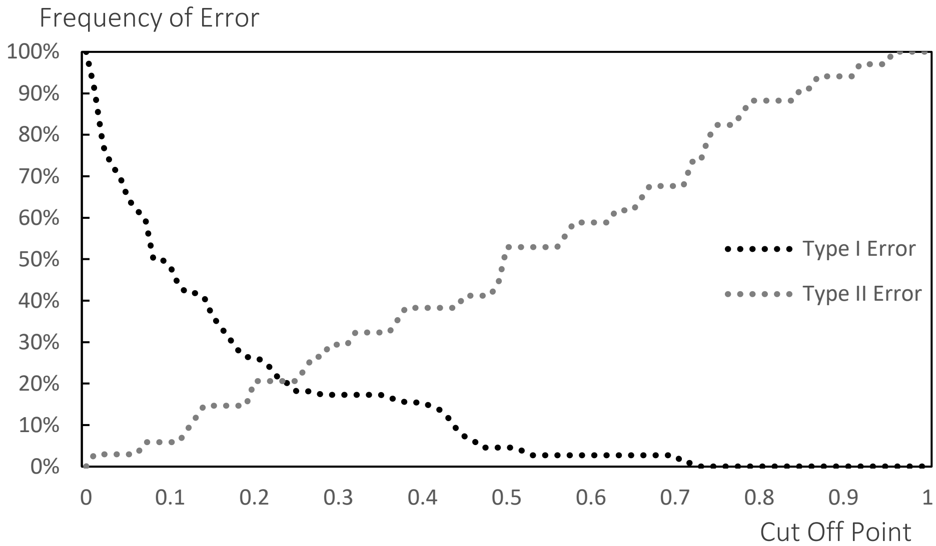


Figure 5: Frequency of Type I and Type II Errors by Cut Off Point



To check the stability of our model we utilize the split-sample testing outlined in Section 4.3.3. The training sample constituting 60% of our data set is based on cases filed between 2003 and 10/2009, and the testing sample constituting the remaining 40% of our sample is based on cases filed between 11/2009 and 2015. The DPM estimated on the training sample was able to classify 85.2% of companies correctly from the training sample with the cut-off point of 0.5. Used on the testing sample, given the same 0.5 cut-off point and the estimates, the DPM correctly classified 83.9%. Detailed results are presented in Appendix A.2. Though the DPM's predictive performance slightly dropped when used on the testing sample, it still retained the ability to discriminate between Chapter 22s and Chapter 11s.

Since our DPM predicts recidivism, the results are not comparable to the general bankruptcy literature. Compared to general literature our study uses a longer time horizon (five years), and financial projections and valuations that are presented in disclosure statements instead of the myopic one-year horizon and historic (pre-bankruptcy) data utilised by most studies. We therefore compare our results only to the literature on recidivism.

Our results corroborate Altman (2014)'s findings that Chapter 22s have significantly worse financial profiles upon emergence than Chapter 11s. Moreover, we show that this is evident from the information that is provided to the court in the disclosure statement, and that it is possible to predict recidivism with good accuracy before the Chapter 11 plan is confirmed.

We believe that our results have considerable implications for current practice. Most importantly, based on section 1129(a)(11) of the Bankruptcy Code, often called 'feasibility criteria', the Chapter 11 plan of reorganization should only be confirmed if it is not likely that the company will re-file or end up in liquidation. In practice, courts opine that this requirement does not imply a guarantee of the Chapter 11 plan's success but rather that there is a reasonable chance of success (Winikka, 2006). We provide evidence that there are cases in which the success of the Chapter 11 plan is highly improbable.

In the past, courts have argued that they do not have the means to independently assess the feasibility of the Chapter 11 plan (Miller, 2002). Our proposed DPM solves this. Our novel DPM uses data that is easily accessible to courts and other parties, and was built to assess the likelihood of recidivism before confirmation of the Chapter 11 plan. We believe that if used, our model could prevent repeated bankruptcies that harm not only creditors but also unrepresented stakeholders such as employees, customers, or suppliers.

6.2 Applications and Limitations

Despite the potential of our proposed DPM, some issues would have to be addressed in practical applications, and there are also some limitations of our study that readers ought to be aware of. Firstly, we have made no assumptions about the difference in costs of mis-classification of Chapter 11s and Chapter 22s, i.e., Type I and Type II errors, respectively. We hypothesise that Type I errors should be less costly than Type II errors. The outcome of Type I mis-classification would likely be the strengthening of the company's capital structure, i.e., a reduction of its *Debt/EV*, which may even be beneficial for the company. However, recidivism is costly for all involved parties. Secondly, our sample size is relatively small, as we only studied the biggest bankruptcies in the United States. Our study should be extended to smaller companies, which would significantly increase the sample size and improve the robustness of the model.

7 Concluding Remarks

In this paper, we examined the impact of financial, ownership, and legal variables on bankruptcy recidivism using a sample of 144 companies, and subsequently developed a distressed predictor model (DPM) to predict bankruptcy recidivism. Unique to our paper, we studied 'Chapter 22' companies prior to emergence from their initial bankruptcy. This was feasible as we utilized the financial projections provided in court disclosure statements during Chapter 11 proceedings.

We found that the four factors traditionally used for bankruptcy prediction (see for instance Ohlson (1980)) - capital structure, operational performance, liquidity, and size, have a substantial impact on recidivism. Perhaps not surprisingly, capital structure in the form of Debt/EV (leverage) plays the most significant role in predicting recidivism. GDP growth before bankruptcy is another important determinant that is also unique to our recidivism prediction. Our results suggest that companies that went bankrupt in a period of economic turmoil are less likely to re-file than those companies that went bankrupt amidst high economic growth. With regard to post-bankruptcy ownership, we did not find conclusive evidence of its impact on recidivism. However, the results hint that companies where activists were owners fared better than those controlled by initial secured creditors. Interestingly enough, we have not found any negative effects of filing for bankruptcy in Delaware or NY SD. On the contrary, recidivism rates in these courts are lower, possibly due to the higher proportion of prepackaged bankruptcies that these courts process. This might be further evidence of the irrelevance of forum shopping, as discussed by K. Ayotte and Skeel Jr (2006) or R. S. Lee (2011).

We constructed a distressed predictor model (DPM) that was able to predict 86.8% of outcomes correctly, compared to the 76.4% of Chapter 11s (companies that have not re-filed) in our sample. Our model extends the findings of Altman (2014), suggesting that there are significant differences between Chapter 11s and Chapter 22s, even before these companies emerge from bankruptcy. We believe that these findings should have an impact on the current practices of the court in relation 1129(a)(11) of the Bankruptcy Code, whereby the feasibility of plans of reorganization are seldom challenged.

Our sample size remains a significant limitation of our study. As we only analysed bankruptcies with pre-petition assets larger than $330 million in 2022 USD, we believe our study could be made more robust by extending the sample to smaller bankruptcies. Additionally, with an extended time horizon, perhaps more could be done to study the differences between Chapter 22, 33 and 44 firms.

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A Appendix - Testing assumptions

A.1 Assumption Testing

A.1.1 Outliers

Table 10: Outliers Testing: Influential Values and Their Standard Residual Values

Cook's Distance	Standard Residual Value
0.05	2.08
0.11	3.13
0.04	2.13
0.03	-1.67
0.04	2.33
0.07	1.27
0.06	1.54
Cooks distance treshold	0.03
Standard residual value treshold	3.00

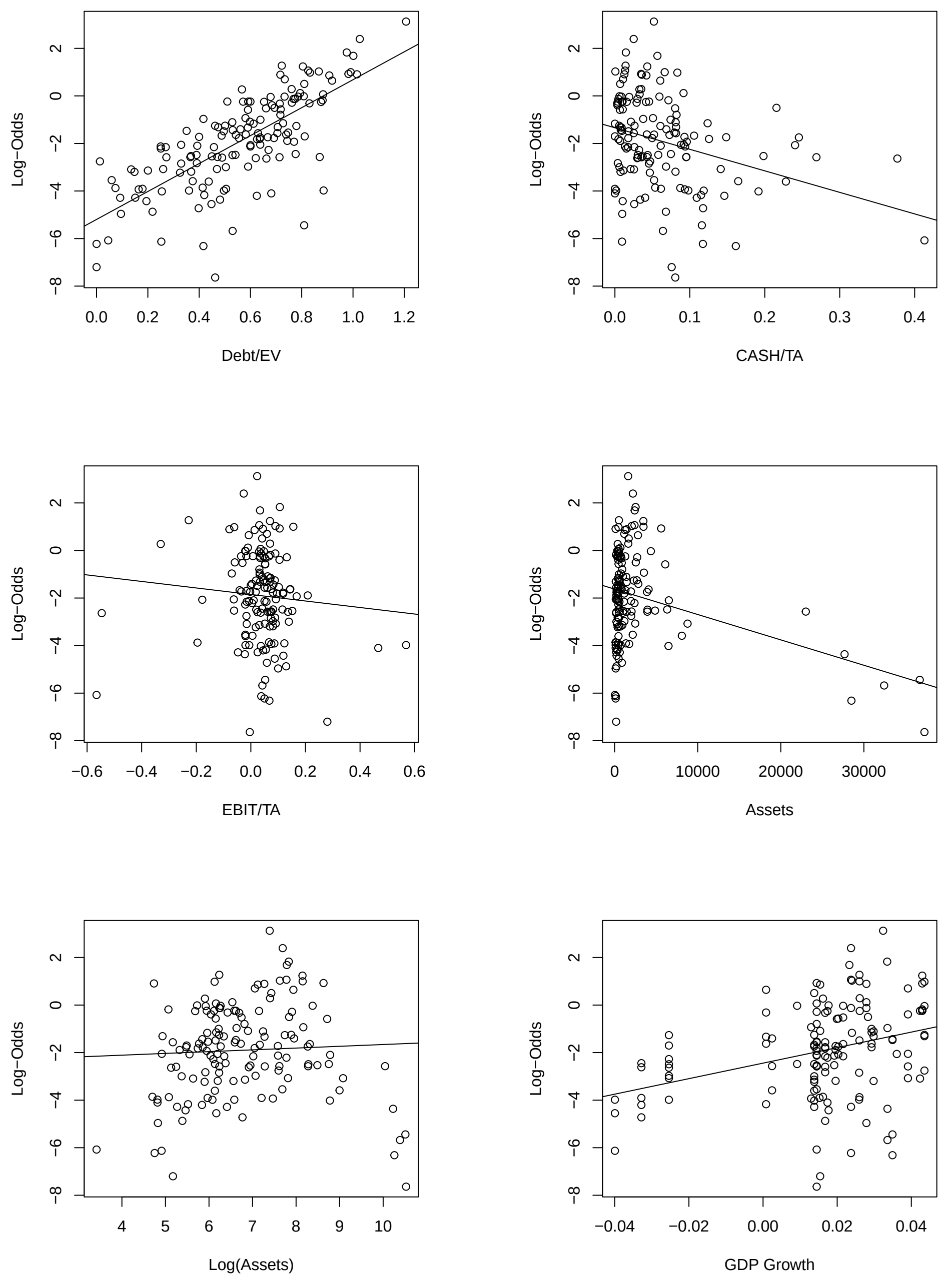
A.1.2 Multicollinearity

Table 11: Testing Multicollinearity

Variable	VIF
DEBT/EV	1.03
CASH/TA	1.12
EBIT/TA	1.13
Assets	2.26
log(Assets)	2.35
Gdp Growth Before	1.08

A.1.3 Linearity

Figure 6: Scatter plots of Independent Variables and Log-Odds



A.2 Stability Testing

Table 12: Training Sample - Proposed DPM

	Dependent variable:
	Re-Filed 5Y
Debt/EV	4.598**
	(1.510)
Cash/TA	−9.069
	(7.433)
EBIT/TA	−0.092
	(5.400)
Assets	−0.0002
	(0.0003)
log(Assets)	0.405
	(0.505)
GDP Growth Before	16.016
	(22.778)
Intercept	−5.998+
	(3.374)
Max Classified	85.2%
Percentage Chapter 11s	76.1%
Cut Off	0.50
Type I Error	3.0%
Type II Error	52.4%
Adjusted Pseudo-R2	8.2%
Observations	88
Note:	+p<0.1; *p<0.05; **p<0.01; ***p<0.001

Table 13: Testing Sample - Proposed DPM

Classified	83.9%
Percentage Chapter 11s	76.8%
Cut Off	0.50
Type I Error	4.7%
Type II Error	53.8%
Observations	56