Bankruptcy Resolution: Misery or Strategy

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Abstract

In this study we explore the explanatory power of a set of covariates relating to firm, judicial, case, geographic, and macroeconomic characteristics in explaining the likelihood of successful bankruptcy resolution. Based upon our analysis, we propose an eight-factor multivariate Probit model that best explains bankruptcy resolution. Subsequently, we investigate the effect of strategic behaviour (proxied by financial benefits) on firms' likelihood of emerging from bankruptcy, and whether financial benefits are endogenous to the emergence likelihood. Test results confirm that firms start acting strategically from one up to four years before filing for bankruptcy in the presence of (repeated) adverse event(s).

Keywords: Bankruptcy Resolution, Strategic Behaviour, Chapter 11 Bankruptcy, Financial Distress, Financial Benefit.

JEL Classification Codes: G11; G33; K2; M00

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1. Introduction

When a firm files for bankruptcy protection under Chapter 11, it may either undergo corporate restructuring to emerge from bankruptcy (signalling positive going concern value), or it may be forced into liquidation. Thus, the immediate concern that comes to the mind of related stakeholders (like investors, creditors, financial analysts, bankruptcy courts etc.) is whether the bankruptcy filing firm will be able to emerge and operate profitably (e.g. Denis and Rodgers 2007). While a vast literature spanning over more than six decades exists on prediction of bankruptcy likelihood (Altman 1968, Hillegeist *et al.* 2004, Gupta *et al.* 2018 etc.), relatively, the literature pertaining to bankruptcy resolution has been overlooked.

This study aims to contribute to the literature on organisational decline, corporate turnarounds (Barker III and Barr 2002), risk-shifting (Gilje, 2016) and finance theories of corporate restructuring (Koh *et al.* 2015) by addressing this gap in the literature. In particular, in the first part of this study, we address this concern by examining the statistical significance of a comprehensive set of variables (firm-specific, case-specific, judicial, geographic and macroeconomic factors) in explaining the likelihood of successful bankruptcy resolution. Subsequently, we propose a parsimonious regression model to predict the likelihood of bankruptcy emergence that shall be helpful to various stakeholders in relevant decision making.

Moreover, the major goal of any bankruptcy law is to prevent abusive or fraudulent uses of the bankruptcy system, or in other words, strategic use of the bankruptcy law. Therefore, it is important to understand the motivations of bankruptcy filing firms; what constitutes "abusive" or "strategic" use of bankruptcy law, and how widespread is this practice. Historically, the stigma associated with bankruptcy filing has led companies to undertake the path of bankruptcy filing only if it has exhausted remaining available options (Sutton and Callahan 1987). However, Delaney (1999) challenges these assertions by conceiving bankruptcy as a strategic weapon used by corporations to use their power in order to avoid current financial burdens, and shift future financial risk towards more vulnerable groups in the society. In the existing literature, there is no clear definition of what constitutes a strategic bankruptcy filing. However, in line with the arguments of Fay *et al.* (2002) and Zhang *et al.* (2015) in context of household bankruptcy, considering strategic behaviour to be a conscious decision to benefit from bankruptcy law shall be a reasonable exposition.

In this context, strategic behaviour may be considered as a two-step decision making process. In the first step, the firm receives adverse noisy signal(s) or shock(s) of experiencing bankruptcy in the near future. Based upon this anticipation, the firm evaluates its likelihood of emerging from bankruptcy in the case of Chapter 11 filing, and updates its debt level to maximise its gain from any subsequent bankruptcy filing. Findings of Adler *et al.* (2013), Reboul and Toldrà-Simats (2016) and François and Raviv (2017) also resonate with this view. Thus, a strategic firm is one, which, in the first step, chooses its debt level after conditioning on the signal(s). In other words, a strategic firm is rational and takes decisions to maximise its benefit. On the other hand, a non-strategic firm chooses debt level without conditioning on the signal; it plans to repay its debt in the absence of any adverse event(s).

Some of the recent literature also resonates with this view and reports evidence pertaining to strategic bankruptcy filing (e.g. Donoher 2004; Ellias 2018) or strategic decision making around the bankruptcy period (e.g. Ivashina et al., 2016; Li and Wang, 2016). Additionally, such strategic behaviour shall be highly desirable in the presence of a higher likelihood of bankruptcy emergence. i.e. in the presence of a *positive relationship between strategic behaviour and the likelihood of successful bankruptcy resolution*. Thus, we cannot rule out the possibility that all bankruptcy filings might not be due to '*misery*', but might well be a '*strategy*' to exploit the judicial system and shift financial risk towards creditors. As this gives distressed firms an opportunity to preserve their going concern status at the cost of losses to their creditors. Hence, in the second part of this study, we explore the possibility of such strategic behaviour in the bankruptcy emergence process.

We empirically address these issues by obtaining bankruptcy resolution data from the UCLA-LoPucki Bankrupcty Research Database (BRD),[1] and relevant financial data from the Compustat database. Our empirical analysis is based upon a relatively long analysis period of 23 years, which includes 401 Chapter 11 filings and 264 successful bankruptcy reorganisations of non-financial firms between 1994 and 2017. To the best of our knowledge, there is no significant research to date that provides a formal analysis of the relative importance of a comprehensive set of variables in predicting the likelihood of successful bankruptcy resolution with the exception of LoPucki and Doherty (2015).

They explore the information content of a comprehensive set of about 70 covariates in explaining bankruptcy resolution of the United States (U.S.) firms that filed for Chapter 11 bankruptcy. They explore these variables in hundreds of combinations to identify the one set that best explains a company's bankruptcy survival likelihood, and propose 11 variables in their final multivariate model. They arrive at the best set by simply looking at the multivariate models with higher pseudo R-squared and statistical significance of covariates at a 10 percent or lower level. Although we build upon their work, we significantly differ from them in several respects: unlike them; i) we follow a systematic/robust multivariate model building strategy based on the Average Marginal Effects (AME) of respective covariates (obtained from univariate Probit regression estimates of respect covariates) as suggested by Gupta *et al.* (2018); ii) we report our proposed multivariate model's classification performance, which is about 94%; iii) arguably our model is numerically more stable and robust, as their model includes 11 covariates, and our parsimonious model gives a within-sample classification

[1] UCLA-LoPucki Bankrupcty Research Database (BRD). The BRD is a data collection, data linking, and data dissemination project of the UCLA School of Law. Most of the data are updated monthly. Further details can be found at: http://lopucki.law.ucla.edu (last visited May, 2018). This dataset has been used amongst others by Xia et al. (2016).

accuracy of about 94% with just 8 covariates; iv) the pseudo R-squared of their model is about 0.26, whereas we report a pseudo R-squared of about 0.55; v) most of the covariates suggested in their model are absent in the multivariate model that we propose based upon a more robust model building strategy; vi) and finally, the most significant difference is that we explore whether financial benefit play any strategic role in firms' likelihood of emerging from Chapter 11 bankruptcy.

Empirical results indicate that, amongst firm characteristics, the ratio of total assets to total liabilities and retail industrial sector have negative impact on a firm's emergence likelihood. Conversely, among geographic factors, shopping for a debtor-friendly court increases the likelihood of emergence. Findings for covariates capturing case characteristics are mixed. The replacement of the CEO after filing for Chapter 11, the presence of a pre-packed or pre-negotiated bankruptcy case, and a high ratio of total Debtor in Possession (DIP) loan to total assets before bankruptcy filing increase the likelihood of emergence. In contrast, announcing the intention to sell the business upon bankruptcy filing, and the length of a bankruptcy case (in years) from filing to plan confirmation, conversion to Chapter 7, or dismissal, dramatically increase the risk of unsuccessful resolution.

Moreover, we make an additional significant contribution to the corporate bankruptcy literature by analysing the role of financial benefit in bankruptcy resolution as a proxy for strategic corporate behaviour in Chapter 11 filings. Our empirical design to test this hypothesis is motivated from a popular study on household bankruptcy decision by Fay *et al.* (2002). They report households are more likely to file for bankruptcy when their financial benefit from filing is higher. As a consequence, we measure financial benefit of a firm as the positive difference between its total liabilities and total assets, otherwise zero. In this approach, a positive relationship between bankruptcy emergence and financial benefit from filing, *ceteris paribus*, is taken as evidence of strategic behaviour; and a positive relationship between unsuccessful bankruptcy resolution and adverse events (such as prolonged poor financial health) is taken as evidence of nonstrategic behaviour. Multivariate Probit estimates show the coefficient of financial benefit is positive and highly significant in explaining successful bankruptcy resolution. Thus, providing support for the presence of strategic behaviour, and its positive associated with firm's emergence likelihood.

However, this simple empirical relationship between bankruptcy emergence and financial benefit does not consider more realistic relationships among financial benefit, adverse events, and strategic behaviour (see Zhang *et al.* (2015) for similar discussion in context of household bankruptcy). For example, financial benefit from bankruptcy filing may go up due to adverse events, regardless of whether a firm is trying to abuse bankruptcy law or not. That is, financial benefit goes up when a firm consciously increases debts before filing, consistent with strategic behaviour; and it also goes up, when in financial difficulties it uses debt to pay for expenses, consistent with nonstrategic behaviour. Moreover, a nonstrategic firm may appear strategic to analysts, if it rolls over debt as long as there is hope of repaying it. This leads to higher measured financial benefit before filing, despite no intention to abuse bankruptcy law. In other words, financial benefit is affected by both strategic and nonstrategic behaviour, and a positive coefficient on financial benefit alone is insufficient to distinguish between the two behaviours.

Our subsequent test (employ the empirical design suggested by Zhang *et al.* (2015) in context of household bankruptcy) partially disentangles the role of financial benefit, adverse events, and strategic behaviour: it allows for a positive relationship between bankruptcy emergence and financial benefit for both strategic and nonstrategic firms, and still may distinguish between the two. However, this test cannot distinguish between strategic firms, and non-strategic firms who may appear strategic due to a non-strategic run-up of debt before filing.

Consequently, if the test result shows that financial benefit is endogenous to bankruptcy emergence, that result can be consistent with both strategic and nonstrategic behaviour. If the test result shows that financial benefit is exogenous to bankruptcy emergence, the result supports non-strategic filing behaviour (and shows that the incidence of both strategic filings and non-strategic filings that may appear strategic is statistically insignificant in the data).

Thus, our subsequent empirical design uses a model in which financial benefit and bankruptcy emergence likelihood are jointly determined, we estimate it using joint maximum likelihood, and test for endogeneity of financial benefit and bankruptcy emergence likelihood. We test for the endogeneity of financial benefit in the context of firms' emergence by developing multivariate Probit models with endogenous regressors. We use financial distress scores (proxied by Altman (1968)'s Z-score) at different lags as instrumental variables (to proxy adverse events). Test results show that the coefficient on financial benefit still remain significantly positive with dramatic rise in its magnitude. Test results also suggests that companies may start acting strategically from one up to four years before filing for bankruptcy, to maximise their gain from subsequent bankruptcy filing.

The remainder of this paper is structured as follows. Section 2 describes datasets, sample and covariates. Section 3 presents empirical results and discussion on the bankruptcy resolution model that we propose. Section 4 examines how companies' strategic behaviour affects their likelihood of emerging from Chapter 11 bankruptcy. Finally, Section 5 concludes this study.

2. Dataset, Sample and Covariates

We build the regression model explaining bankruptcy survival using the UCLA-LoPucki Bankrupcty Research Database (BRD) and Compustat database to: i) identify the set of factors explaining firms' emergence likelihood from Chapter 11 bankruptcy filings; ii) evaluate whether strategic emergence is amongst the conditions that best predict companies' emergence prospects by looking at the role of financial benefit; and, iii) test whether financial benefits are endogenous to companies' likelihood of emerging from bankruptcy. The BRD contains data on more than 1,000 large public companies (assets worth $100 million or more, measured in 1980 dollars) that filed for bankruptcy since October 1, 1979. Coverage includes cases filed under Chapter 7 and Chapter 11, whether filed by debtors or creditors, whilst the Compustat Database contains financial information of active and inactive companies since the year 1962.

2.1. Sample Description

We exclude Chapter 7 bankruptcy filings, as they involve outright liquidation, and focus only on companies that filed for Chapter 11 bankruptcy protection. Additionally, we consider only those factors that are available at the time of bankruptcy filing or shortly thereafter. We exclude all cases in which bankruptcy resolution outcome (variable "*EMERGE*") and/or firm identifier (GvkeyBefore[2]) are missing in the BRD database. We also exclude cases in which the filing takes place before 1994, as an important variable "*SALEINT*" – which indicates the debtor intention to liquidate the company at the time of bankruptcy filing, is missing. Since firms generally stop reporting financial statements in years close to filing for bankruptcy, we employ the most recent available information before the filing year in case this data is missing.

This allows us to perform our empirical analysis using a relatively long analysis period of 23 years, which includes 401 Chapter 11 filings and 264 successful bankruptcy resolutions of non-financial firms between 1994 and 2017 (see Table 1). Over this time window, the emergence rate of companies does not seem to follow a clear pattern. Indeed, as reported in Table 1, which illustrates year-wise distribution of firms filing for Chapter 11, and the ones emerging from it. The proportion of firms emerging changes without a regular trend over the

[2] In BRD, GVKEY is a Standard & Poor's identifier for a 10-K filing company. GVKEYs can be used to download data on the company from Compustat and other sources. GvkeyBefore is the GVKEY for the filing company.

years, hence shall be useful to investigate the set of predictors explaining the probability of emergence from Chapter 11 bankruptcy.

[Insert Table 1 Here]

2.2. Selection of Covariates

2.2.1. Dependent Variable: Defining Bankruptcy Emergence

Bankruptcy filing firms can choose between filing for Chapter 7 (which involves the liquidation of the debtors' property by a court-appointed trustee and makes payments to creditors based on law) or Chapter 11 (in which firms retain their going concern status, propose a repayment plan and get discharged from remaining debt once the plan is completed) bankruptcy. Firms filing for Chapter 11 bankruptcy protection face two options: to either resolve the cause and emerge, or liquate their assets (Bryan et al., 2002). According to the provisions of the U.S. Bankruptcy Code, four bankruptcy reorganisation outcomes are possible: i) *successful reorganisations*: firms maintain their corporate identities, continuing as publicly traded firms on national stock exchanges; ii) *partially successful reorganisations*: firms which maintain their corporate identities but fail to meet one or more of the other qualifications stipulated for classification as a successful reorganisation; iii) *mergers or acquisitions*: firms which publicly report as being acquired by previously existing firms; and, iv) *liquidations*: firms which are publicly reported as liquidated or which have no identifiable successor business. In light of this classification, we consider emergence from bankruptcy if a firm either reorganises itself or has been acquired/merged. It indicates a 'continuation – with intent to continue indefinitely – of the debtor's business operations after the debtor emerges from bankruptcy' . More specifically, our dependent variable $EMERGE_{it}$ is measured as an indicator variable, which equals 1 if firm i has been reorganised or acquired/merged, 0 otherwise.

2.2.2. Independent Variables: Predictors of Bankruptcy Emergence

Each year, hundreds of companies declare bankruptcy in the United States. If we take into account all stakeholders' interests, the emergence of companies seems to be more economically desirable than liquidation whenever survival is achievable . Given the number of companies declaring bankruptcy, and their impact on society, previous studies have devoted some attention to identifying the factors affecting the outcome of successful bankruptcy reorganisation. However, this task has not been easy due to information asymmetry and the damaged reputation of bankruptcy filing firms (Trahms et al., 2013; Xia et al., 2016). In the following section, a survey of the factors that could potentially explain firms' emergence from bankruptcy is drawn.

A wide range of factors could play a role in predicting firms' emergence from bankruptcy, at the time of this adverse event or shortly after a company files for Chapter 11. From juxtaposing literature on organisational decline, corporate turnarounds and corporate restructuring, we identified five categories of potential predictors of bankruptcy resolution outcomes: i) firm-specific; ii) judicial; iii) case-specific; iv) geographic; and v) macroeconomic. In particular, we primarily consider those factors that are explored in LoPucki and Doherty (2015) to explain successful bankruptcy resolution of the U.S. firms. See Appendix A1 to get a snapshot of all covariates explored in this study.

2.2.2.1. *Firm characteristics*

To capture how a firm's characteristics can affect its bankruptcy survival likelihood, we focus on five main features of a firm (size, financial fragility, operating profit, organisational structure and industry) on which empirical literature looking at the determinants of bankruptcy emergence typically concentrates.

In the literature on bankruptcy survival, *company size* is captured by its assets (e.g. Dahiya et al., 2003). This stream of research reports positive and significant correlations between company size and its bankruptcy survival likelihood. In particular, Denis and Rodgers (2007) highlight that larger firms are more likely to reorganise and emerge from Chapter 11, rather than being acquired or liquidated. They attribute this positive impact of the size of the company on its bankruptcy survival likelihood to the mechanism by which large companies tend to engage with a broader variety of activities, providing them with more options for change. We measure firm/debtor's size (*CSIZE*) as the log of a debtor's total assets in current dollars, as reported on the debtor's last annual report before filing bankruptcy.

The *leverage before bankruptcy* has been reported to be of pivotal importance for a company's emergence . The level of leverage reflects the financial position of firms; in turn, it defines their capacity to raise new capital through borrowing and meet debt obligations. Firms with high costs choose low leverage to avoid distress and retain exposure to the systematic risk of bearing such costs. In the case of distress, low-leverage firms are worst off compared to high-leverage firms in terms of the deterioration in their accounting operating performance and increase in exposure to systematic risk (George and Hwang, 2010). Previous studies show the presence of a 'distress risk puzzle', that is: returns are lower for firms with greater distress intensities. The puzzle springs from the fact that firms with high distress intensity or nearness to default have exhausted their capacity to issue low-risk debt. 'Since leverage amplifies the exposure of equity to priced systematic risks, firms with high distress measures should be those for which equity exposures are most amplified' Le Mens et al., 2011). Similarly to the company size, Denis and Rodgers (2007) report that companies that show higher liability ratios before filing for Chapter 11 are more likely to reorganise than to liquidate or be acquired. To measure the financial fragility of firms, we use the ratio of total assets to total liabilities (*TATL*) before filing bankruptcy as reported on the debtor's last annual report before filing bankruptcy. Drawing upon , this variable – built as a transformation of equity – can be considered a useful proxy of 'leverage before bankruptcy'.

Firms' survival can be affected by their profitability. *Earnings Before Interest and Taxes* (*EBIT/*operating profit) identifies a measure of a company's profitability. It represents an accurate measure of the expenses that a debtor must cover to survive as it considers depreciation and amortisation . Operating income is considered the most direct measure of economic distress. The presence of a negative EBIT (that is, operating losses) can lead to a conversion to Chapter 7 liquidation as the company show its impossibility to cover its post-bankruptcy debt, which is necessary for reaching long-term sustainability . Thus, we consider whether a debtor's EBIT in the previous year before filing bankruptcy is greater than zero (*PEBIT*), thus we assign *PEBIT* equal to 1 for EBIT > 0, or 0 otherwise.

Prior research on bankruptcy emergence shows that companies have a higher probability of emerging if they are large (e.g. Yu and He 2018). There can be multiple explanations for this result. Firstly, large companies with a higher probability of emerging can buy assets using funds raised through prior, unsecured bond offerings. Secondly, they may possess more specialised assets, which accordingly reduces the number of buyers interested in these assets. Thirdly, large firms are more likely to receive government aid due to their national strategic importance. Fourthly, large firms own more assets available for collateral to secure claims, which they can sell to increase their survival likelihood. We consider size in terms of organisational structure (*EMP*) as a natural logarithm of the number of persons employed by the debtor as of the last 10-K before filing for bankruptcy.

Finally, the industrial sector in which a firm operates might affect the likelihood of its emergence (Yu and He 2018) or failure (Gupta and Chaudhry 2019). For instance, manufacturers present a higher success rate compared to other types of business (LoPucki and Doherty 2015). In their work, they looks at five industrial categories: construction, transportation, retail/wholesale, service, and manufacturing/mining. they finds companies operating in construction and manufacturing/mining industries have a lower likelihood of emerging. They also analyse the impact of operating in the retail sector on emergence; their results seem to highlight a negative (but statistically insignificant) relationship. To define the list of industrial sectors (*INDUSTRY*), we draw upon the work of Gupta and Chaudhry (2019) to categorise our sample of firms into seven industrial sectors as indicated in Table 2. This variable is a factor variable built using a Standard Industrial Classification Code of the U.S. firms.

[Insert Table 2 Here]

2.2.2.2. *Juridical Characteristics*

One of the main tasks undertaken by Bankruptcy Courts is to foster conflict resolution and hinder opportunism. Once companies declare bankruptcy, all unilateral actions by creditors are suspended and a lower level of unanimity (compared to the voluntary restructurings) for reorganisation is required. It is the judge presiding over the case who signs the order confirming the plan, dismissing it or converting the case. A judge's experience can have a positive effect on litigation (Choi et al., 2013) – amongst which bankruptcy litigation – as well as on emergence. In order to take into consideration the impact of judicial ability on a company's emergence, we examine three possible predictors. Firstly, *JEXP* – a natural logarithm of the number of cases the judge has completed at confirmation of the instant case. It captures the judge's experience. This variable has been built based on the "*JudgeDisposition"* variable of the BRD, which reports the full name of the bankruptcy judge who entered the order disposing of the Chapter 11 case. Secondly, *JEXPD* – a dummy variable, which equals 1 if the judge has completed more than 5 cases; 0 otherwise.

Similarly, in some model specifications, LoPucki and Doherty (2015) find that the experience of the debtor's attorney could positively impact the company's emergence from Chapter 11. We capture the attorney's experience (*AEXP*) by computing the natural logarithm of the number of cases the lead counsel (who represented the Debtor-in-possession – DIP – in filing of the bankruptcy case) or the attorney has handled before the case being considered.

2.2.2.3. *Case Characteristics*

In bankruptcy literature, several characteristics linked to the specificity of the case being considered seem to impact a firm's bankruptcy emergence likelihood. The first set of predictors is directly linked to the company itself and its managerial strategy, the second one deals with the specific treatment the company is given during the bankruptcy court process.

On the first set of predictors, the company's governance – and its potential renewal during the bankruptcy process – as well as an intention to sell the business are crucial for its survival (LoPucki and Doherty 2015). In particular, the CEO figure is key (see Maskara and Miller 2018). Executives in declining firms may engage in ship-jumping behaviour (i.e., voluntarily move to new employers before the failure occurs) to avoid the stigma of failure (Jiang et al., 2017). The rate of director turnover in the five-year period prior to the corporate bankruptcy is also reported to be substantially higher for bankrupt firms. Previous studies also suggest that removal of the extant management as a turnaround strategy in financially stressed firms is quite common as well (see Trahms *et al.* 2013). Maintaining the same CEO could lead the company to 'threat-rigidity' responses and could deprive it of executives best suited to initiating strategic changes (see Sarkar and Osiyevskyy 2018). Additionally, Arora (2018) claims that when a company deals with a crisis, its stakeholders may reconsider the trust placed in management and internal directors, and start looking for signals from more independent and credible sources. In this context, the author suggests that the role of financially linked independent directors takes on a more important role. Indeed, they can provide firms with a higher likelihood of re-emergence thanks to their effort and their credibility with financial institutions. However, changes in CEO's contractual provisions may also enable creditors of financially distressed firms to retain highly skilled CEOs with firm-specific knowledge, and provide them with incentives to improve firm performance (Evans III *et al.* 2013). We account for the impact of a company's governance on a company's emergence based on the following two predictive variables. Firstly, *CEOR* – a dummy variable equalling 1 if the CEO at filing was replaced by another CEO or another manager after the date on which the debtor's CEO at filing ceased to be the CEO; and 0 otherwise. Secondly, *CEODA* – represents the number of days (expressed in years) from which the CEO filing bankruptcy ceased to be the CEO from the day on which the bankruptcy case was filed.

Additionally, as reported by James (2016), intangible assets as well as Section 363 *asset sales* are associated with a shorter duration in bankruptcy. An explanation of these results can be found from the fact that firms have greater incentives to undertake bankruptcy as a strategic choice to protect the interests of key stakeholders (employees, customers, and suppliers), as values of these assets are closely tied to relationships with these actors. Declining firms divest better than survivors but, at the same time, infusion of fresh capital might be helpful in raising resources more effectively, preventing firms from falling into a liquidity trap (see Gilson 2012). Due to weaker bargaining power with suppliers and other constituents, small firms are more likely to stop operations (called organisational death) after filing for Chapter 11 and be forced to liquidate their remaining (see Franks and Sussman 2005). LoPucki and Doherty (2015) argue that companies tend to avoid stating an intention to sell as the market can interpret this action as a signal of weakness. Indeed, weaker companies show their intention to sell as they desperately need buyers. Given that the decision making is a self-reinforcing process of bankruptcy, project weakness in the eyes of a company's stakeholders could hinder emergence. Thus, we consider a company's intention to sell (*SALEINT*) as a dummy variable equal to 1 if, at the time of filing, the debtor publicly indicated an intention to sell or liquidate all or a substantial portion of its assets, and 0 otherwise.

On the second set of predictors, previous studies report the incidence of the decision undertaken in court. Firstly, the presence of a pre-packaged or pre-negotiated case (i.e. a specialised Chapter 11 filing where companies negotiate a reorganisation plan with its creditors before filing for bankruptcy) significantly influences the likelihood of a successful bankruptcy resolution. This tends to reduce the costs and duration of the entire reorganisation process while retaining the advantages of legal bankruptcy (see Teloni 2015). We measure the presence of a pre-packaged or pre-negotiated case (*PREAGR*) as a variable equal to 1 for a pre-packaged or pre-negotiated case, and 0 for a free fall case. Secondly, the length of the bankruptcy process, filing date and the confirmation date of a Chapter 11 re-organisation is also considered. The longer the duration the lower the possibility of emerging for a company. Duration (*DURATION*) has been computed as the number of years between the filing date and either the confirmation date of a Chapter 11 re-organisation, or the date on which the Chapter 11 case was converted to Chapter 7 or dismissed. Thirdly, the appointment of a *creditors' committee* by the U.S. Trustee could negatively impact the bankruptcy survival puzzle as the resistance of the committee to debtors' efforts to reorganise could cause company failure (LoPucki and Doherty, 2015). In our models, the variable *CCOM* considers whether an official committee is appointed to represent the unsecured creditors prior to case disposition. It equals 1 if the U.S. Trustee has appointed a creditors' committee to represent the unsecured creditors prior to case disposition; 0 otherwise. Fourthly, the presence and level of the loan outside the ordinary course of business is considered. A firm during bankruptcy reorganisation is known as the debtor-in-possession (DIP) 'because a creditor has a lien against the property in its possession. The DIP continues to run the business and has the powers and obligation of a trustee to operate in the best interest of creditors'. The DIP financing is a mechanism of secured financing available to distressed firms, created to manage financial uncertainties as well as to scale down the lending disincentives of potential creditors that emerge during the bankruptcy process . It provides companies with a tool which gives them more flexibility to manage their retrenchment and strategic actions more efficiently (see Dahiya *et al.* 2003). We capture the presence of the loan outside the ordinary course of business (*DIPL*) as a dummy variable equalling 1 if the court has approved DIP borrowing outside the ordinary course of business, and 0 otherwise. We also explore the explanatory power of a scaled version of DIP loan (*DIPTA*) as the ratio of total DIP loan received to total assets before bankruptcy filing. This measure of DIP loan obtained per $ of total assets is arguably a better measure than *DIPL*.

2.2.2.4. *Geographic Characteristics*

As suggested by the literature on bankruptcy, the geographical environment in which the company operates as well as the bankruptcy court serving the case affects the company's bankruptcy survival likelihood (e.g. Coordes 2015). As indicated in LoPucki and Doherty's (2015) work, the geographic location of the court where the litigation takes place could affect a company's emergence. In particular, the authors claim that Delaware (Washington) and the Manhattan Division of the Southern District of New York are the two principal destinations for forum shopping by large public companies. From their empirical evidence, it emerges that companies filing in these two courts are significantly more likely to survive. As reported by Boettcher et al. (2014), these two districts – which have favourable policies toward business – compete to attract firms to incorporate and file bankruptcies in their states. Judges in these debtor-friendly districts are more likely to decide in the corporation's favour during bankruptcy proceedings. Filing either in Delaware or in New York allows companies to avoid much of the state tax in their headquarter state, as well as providing benefit from the less restrictive laws of other states (LoPucki, 2006). Boettcher et al. (2014) report how debtor-friendly practices could lead companies to emerge from bankruptcy, without careful analysis, even in cases in which the plans have little chance of success. These types of courts induce negative externalities for society overall, such as increasing refiling rates, lowering credit ratings and lowering sales growth (Chang and Schoar, 2006). For these reasons, we take into consideration the following geographical dimensions. Firstly, we consider the city in which the case was filed (*CFILE*). This variable is categorised as Delaware (DE, 1), New York (NY, 2) and all other cities (OT, 3). Secondly, we consider the distance between the debtor's bankruptcy court and Wilmington, DE (*HCCTODE*). *HCCTODE* is computed as the natural logarithm of the distance (expressed in number of miles) between the debtor's bankruptcy court to which the debtor's case has been assigned and Wilmington, DE. It is measured as the crow flies. Finally, we consider the presence of bankruptcy shopping (*BSHOP*). BSHOP equals 1 if the city in which the case was filed does not match the location of the bankruptcy court to which the debtor's case has been assigned, 0 otherwise.

2.2.2.5. *Macroeconomic Characteristics*

Aysun (2014, 2015) explore the link between bankruptcy resolution capacity and economic characteristics, and report significant role of macroeconomic conditions on the likelihood of bankruptcy resolution. Further, LoPucki and Doherty (2015) empirically document the existence of a relationship between interest rates and bankruptcy survival. They report that when the prime rate of interest one year before the bankruptcy petition date is low, companies show a higher probability of emergence. Thus, we include two variables on interest rates as they capture the state of the economic environment in which the company operates, and have an impact on bankruptcy survival. Firstly, we include *PRIME1* – the prime rate of interest one year before the case filing. Secondly, we include *PRIMEF* – the prime rate of interest on the bankruptcy filing date.

3. Probit Model of Bankruptcy Emergence

3.1. Descriptive Analysis

We first inspect descriptive statistics to evaluate the variability of covariates and the potential biases that may arise in the multivariate set-up due to any unexpected variability. Descriptive measures of respective covariates for emerged and non-emerged groups of firms reported in Appendix A2 are in line with our expectation (see Appendix A2). However, the correlation matrix in Table 3 shows that some covariates exhibit moderate-to-strong correlation with other covariates, primarily due to their construction. In particular, JEXP shows a strong positive correlation of approximately 0.85 with JEXPD and DIPL with DIPTA (0.7002). PRIME1 is strongly positively correlated with PRIMEF (0.7180), whilst EMP exhibits a moderate positive correlation with CSIZE (0.5099). Amongst the negative correlations, we highlight moderate correlation in the case of CFILE with JEXP (-0.5572) and JEXPD (-0.5170), supporting the argument that the bankruptcy courts located in other cities but DE and NY are associated with judges with less experience (in terms of number of cases completed at confirmation of the case being considered). Similarly, BSHOP and CFILE (-0.6714) show a strong negative correlation confirming that bankruptcy courts located in other cities except DE and NY are associated with bankruptcy shopping. Prepackaged or prenegotiated cases are negatively associated with the appointment of a creditors' committee to represent the unsecured creditors prior to case disposition (-0.5231). Finally, a moderate correlation is observed between PRIME1 and DIPL (-0.5441) due to the negative relationship between interest rate and desire for credit. Therefore, issues associated with multicollinearity need to be addressed carefully in the development of multivariate models, which we discuss in Section 3.3.

[Insert Table 3 Here]

3.2. Univariate Probit Regression and Average Marginal Effects

In order to gauge the explanatory power of respective covariates and facilitate the specification of subsequent multivariate models, we first report univariate Probit estimates for all covariates along with their Average Marginal Effects[3] (AME). The results of univariate regression estimates are presented in Table 4.

[Insert Table 4 Here]

Considering firms' characteristics, the univariate regression results show a positive relationship between firms' emergence likelihood and a debtor's total assets size (CSIZE), as well as with positive EBIT before filling (PBEIT). A positive bivariate relationship is also found between EMERGE and EMP. Indeed, a 1% increase in the number of employees is associated with about a 3% increase in a firm's emergence likelihood. Conversely, a rise in the ratio of total assets over total liabilities before filing bankruptcy (TATL) reduces companies' likelihood of emergence, as an increase in assets makes liquidation more desirable to creditors. Regarding the variable INDUSTRY: all six industrial dummies are highly insignificant in joint estimation. Thus, we test the statistical significance of respective industrial classification from 1 through to 7 (listed in Table 2) as a dummy variable (for instance, in the case of manufacturing firms, all firms with code 4 are assigned 1 and the remaining are assigned 0), and find that manufacturing and retail dummies are significant. Also, a factor variable, with three classification levels of manufacturing, retail and a reference category, is insignificant as well. Thus, we include a dummy variable corresponding to retail industrial classification (INDUSTRY-R) in our multivariate models as its absolute AME reported in Table 4 is higher than the absolute AME of manufacturing firms (INDUSTRY-M). For similar reasons, we include CFILE as a dummy variable equalling 1 for 'OT' category and 0 otherwise.

[3] In non-linear regression analysis, marginal effects are a useful way to examine the effect of changes in a given covariate on changes in the outcome variable, holding other covariates constant. These can be computed as marginal change (it is the partial derivative for continuous predictors) when a covariate changes by an infinitely small quantity and discrete change (for factor variables) when a covariate changes by a fixed quantity. AME of a given covariate is the average of its marginal effects computed for each observation at its observed values. Alternatively, AME can be interpreted as the change in the outcome (company's emergence = 1, in our case) probabilities due to unit change in the value of a given covariate, provided other covariates are held constant. See Long and Freese (2014) and Gupta et al. (2018: 451) for detailed discussion on this topic.

Juridical characteristics (JEXP, JEXPD, and AEXP) exhibit a positive and statistically significant relationship with EMERGE. The result, in reference to judicial experience (JEXP), confirms previous studies showing that the likelihood of emergence increases with the number of case a judge presides over.

Mixed results are present for case characteristics. CEOR, CEODA, PREAGR, DIPL and DIPTA show positive explanatory power; conversely, SALIENT, DURATION, CCOM have a statistically significant but negative impact on companies' emergence likelihood. Some of these results are in line with the findings of previous studies: in particular, in the case of a pre-packaged or pre-negotiated bankruptcy, and in a case in which a company indicates its intention to sell the business (SALEINT); or when the court approves DIP borrowing outside the ordinary course of business (DIPL). In particular, SALEINT is confirmed as being the strongest single predictor of failure during bankruptcy. In contrast, our univariate regression results show discordant findings in the case of a U.S. Trustee appointed creditors' committee to represent the unsecured creditors prior to case disposition (CCOM). This negative relationship show that companies are more likely to confirm a liquidation plan if a creditors' committee is appointed.

If we consider the geographic characteristics, empirical results seem to highlight that BSHOP has a positive and statistically significant impact on bankruptcy emergence. This indicates that the presence of bankruptcy shopping is associated with about a 12% increase in a firm's emergence likelihood. The importance of the location of court is further supported by the negative bivariate relationship between a company's emergence with both HCCTODE and CFILE in all other cities except New York and Wilmington, Delaware (CFILE OT). Indeed, the farther away a debtor's bankruptcy court is from Wilmington (one of the principal destinations for forum shopping) the lower the probability of emergence. Accordingly, bankruptcy filings in cities other than New York and Wilmington negatively predict companies' survival.

Finally, both variables capturing the macroeconomic environment, PRIME1 and PRIMEF, are highly significant predictors and show negative signs suggesting that the higher the prime rate of interest one year before case filing and at the filing date, the lower the likelihood of emergence.

3.3. Multivariate Probit Model

Considering the nature of our investigation, we use a simple Probit specification to model the likelihood of a firm emerging from Chapter 11 bankruptcy as follows:

$$(1) \qquad EMERGE_i = f(\gamma F_{it} + \delta J_{it} + \phi C_{it} + \eta G_{it} + \varphi M_{it} + u > 0)$$

This specification allows us to investigate companies' emergence ($EMERGE_i$) likelihood as a function of a set of firm (F), judicial (J), case (C), geographical (G) and macroeconomic (M) characteristics. To narrow down the list of covariates found significant in the univariate analysis, we follow the multivariate model building strategy suggested by Gupta et al. (2018).

We first rank competing variables based on the magnitude of their AMEs.[4] We then introduce each variable at a time into the multivariate model in descending order of magnitude, and simultaneously eliminate covariates that do not meet our prespecified criteria. The rationale is that the higher the value of AME, the higher the change in the predicted probability due to the unit change in the covariate's value. Thus, a covariate with a higher value of AME (e.g. DIPTA in Table 4) is more efficient in discriminating between emerging and non-emerging groups of firms than a covariate with a lower value of AME (e.g. DURATION in Table 4).

[4] The standard error of a model increases with the increase in the number of covariates, and this also makes the model more dependent on the observed data. Thus, the objective should be to employ a minimum number of covariates for a desired accuracy level (see chapter 4 of Hosmer Jr et al., 2013).

Among the prespecified criteria, we exclude a covariate from the multivariate model if, when introduced: i) it affects the sign of any previously added covariate; ii) it bears the opposite sign to that in the univariate regression; iii) it bears the expected sign but has a p-value greater than 0.10; and, iv) it makes a previously added covariate insignificant with a p-value greater than 0.10. This method of covariate introduction while developing multivariate models reasonably addresses the multicollinearity problem, and provides a parsimonious set of covariates explaining the variance of the outcome variable .

This gives us a parsimonious multivariate Probit model with eight covariates, all of which are highly significant (see Table 5) in explaining bankruptcy resolution likelihood. Within the firm characteristics, TATL and operating in retail sectors (INDUSTRY-R) have a negative and statistically significant impact on companies' emergence. Conversely, looking at the geographical characteristics, it emerges that cases whose forum shops to a court away from the debtor's headquarters increases the likelihood of emergence. This result confirms the findings of the univariate specification by reinforcing the critical role played by the location of the court to which the case is assigned. The empirical results for covariates capturing case characteristics are mixed. The replacement of the CEO after filing for Chapter 11 carries a positive coefficient with a statistically significant result at a 99% level. This supports the importance of releasing the company from potential 'threat-rigidity' by injecting fresh management resources to initiate strategic change. A positive effect on a company's emergence is also found in the case of a pre-packed or pre-negotiated bankruptcy (PREAGR) as its initialisation tends to reduce the costs and duration of the reorganisation process. The higher the ratio of total DIP loan received to total assets before bankruptcy filing (DIPTA), the higher the likelihood of emergence. This seems to sustain the importance of providing bankrupted companies with a wider flexibility to manage their retrenchment and undertake strategic action via the use of DIP financing tool. The length of a bankruptcy case in days from filing to plan confirmation, conversion to Chapter 7, or dismissal (DURATION) predict an increase in the probability of a company's emergence. In accordance with LoPucki and Doherty (2015), announcing the intention to sell a company's business dramatically increases the risks of unsuccessful resolution.

None of the juridical and economic predictors qualify for inclusion in the multivariate specification. As a robustness check, we re-estimate the final Probit model with Logit specification (see columns 5, 6 and 7 in Table 5). Results obtained in the Probit specification hold in the Logit one as well. Furthermore, as indicated by Gupta et al. (2018), we evaluate the classification performance of our multivariate model using a non-parametric classification measure, namely Area Under Receiver Operating Characteristic Curve (AUROC). As reported in Figure 1, the area under AUROC curve for this model is about 94%, suggesting excellent classification performance of our multivariate model.

[Insert Table 5 and Figure 1]

4. Strategic Behaviour in Bankruptcy Resolution

The possibility that managers can deliberately use bankruptcy as an effective strategy for dealing with financial distress has been investigated (Moulton and Thomas, 1993: 125) since the implementation of the Bankruptcy Reform Act of 1978 (e.g. Flynn and Farid 1991). As described in the model elaborated by Zwiebel (1996), when managers perceive bankruptcy as an inevitable outcome, they become more likely to undertake inefficient activities that might confer them personal benefits (even if detrimental for both debtholders and shareholders). Given managers' control over both information and action, delayed filings may represent opportunistic behaviour on their part rather than pursuit of firms' wealth preservation (Moulton and Thomas, 1993). Zwiebel (1996) suggests that the fraudulent diversion of funds, such as corporate 'looting' – which diverges from standard risk-shifting asset-substitution activity (Akerlof *et al.* 1993), can be considered a manifestation of this action. For cases in which the bankruptcy is approaching, the model by Akerlof *et al*. (1993) predicts that a manager-owner will engage in looting if the amount that can be looted exceeds the value of equity under optimal decisions (Zwiebel, 1996). The implementation of these fraudulent activities, such as setting a debt level too high for personal gain leading to bankruptcy, increases as managers gets closer to the end of tenure (Zwiebel, 1996). Distressed firms are usually characterised by the presence of abnormally large leverage ratios and small proportions of equity over their capital structure (Li *et al.* 2017). This means that shareholders push the company to undertake risky projects as they have little to lose. Indeed, if the investments fail, the bondholders will be the ones to bear the cost; conversely shareholders loss will be limited to their stake in the firm upon bankruptcy (Li *et al*. 2017).

From an organisational perspective, companies could also proactively file for Chapter 11 to preserve or boost their value. In recent years, persistently poor performing firms have been reported to file for bankruptcy for strategic reasons (James, 2016). Previous studies have identified several rationales behind this instrumental use of bankruptcy (Gilson 2010, Evans and Borders 2014). Indeed, firms could strategically contemplate filing Chapter 11 as a viable strategic option for long-term survival (Flynn and Farid, 1991), leading them to realign a company's structure with their strategic competencies, annihilating competition (Borenstein and Rose 2003), or even negotiating better terms with stakeholders (Delaney, 1999) which, in turn, provides them with a higher likelihood of emerging from bankruptcy (Flynn and Farid, 1991: 73). For instance, companies in financial distress that culminate in a bankruptcy might decide to apply lower prices to compete aggressively (Borenstein and Rose, 2003). The protection offered by Chapter 11 may also act as a temporary buffer from environmental pressures. The reduction of creditor demands frees financial resources allowing companies to deal with the competitive environment more effectively (Flynn and Farid, 1991). For instance, the implementation of Section 363 of the U.S. Bankruptcy Code could enable companies to sell difficult-to-trade assets, thus freeing companies from barriers that could represent obstacles to the negotiation of fair value in an out-of-court asset sale (Eckbo and Thorburn 2008). Moreover, as tested by James (2016), declining firms are more likely to reorganise in bankruptcy (and subsequently emerge as a going concern) both when they have unfavourable relationships and/or contract arrangements with stakeholders, and when they can reject unfavourable contracts with these stakeholders.

In summary, filing for Chapter 11 originates both benefits and costs to the company. The main benefit is that, once a firm files for Chapter 11, creditors cannot act against the firm unless approved in the reorganisation plan indicated by the court. This releases the company from any further collection attempts, lawsuits and foreclosure procedures. Additionally, the filing also enables debtors to borrow new debt via the 'Debtor-in-Possession' provision (DIP financing). Whilst the costs are the same for all types of company, the benefits are significantly higher for low-value firms than high-value firms. In equilibrium, all low-value firms file for Chapter 11 voluntarily and high-value firms do not file. Indeed, as the model elaborated by Li (2013) on voluntary Chapter 11 filing shows, by filing Chapter 11, low-value firms reveal adverse information (namely, true firm value) to shareholders through a 'signalling' effect.

Considering the discussion above, we cannot rule out the possibility that all bankruptcy filings might not be due to 'misery', but might well be a 'strategy' to exploit the judicial system and shift financial risk towards providers of debt capital. Additionally, such strategic behaviour would be highly desirable in the presence of a higher likelihood of bankruptcy emergence, as this would give distressed firms an opportunity to preserve their going concern status at the cost of losses to their creditors. Hence, we subsequently explore the possibility of such strategic behaviour in the bankruptcy emergence process. In particular, we explore whether strategic bankruptcy filing (investigated using financial benefits) is amongst the conditions that best predict firms' likelihood of emerging from bankruptcy; and if so, whether financial benefits are endogenous to companies' bankruptcy emergence likelihood.

1.1. Financial Benefit and its Role in Bankruptcy Resolution

Adler *et al.* (2013) report that, in anticipation of bankruptcy, firms tend to increase their level of debt in years before the bankruptcy filing year. This eventually allows them maximize financial benefit in the event of bankruptcy reorganisation. Intuitively, it appears that higher the amount of debt the lower shall be the likelihood of a successful bankruptcy resolution. If we compute a firm's financial benefit from bankruptcy filing as follows:

$$\text{(2)} \qquad \textit{Financial Benefit}_{it} = \text{maximum } [(TL_{it} - TA_{it}), 0]$$

where $\textit{Financial Benefit}_{it}$ is the financial benefit from filing for company i in the period t, TL_{it} is the total liabilities of company i in the period t and TA_{it} is the total assets for company i in the period t. Then, we would expect a negative relationship between financial benefit and firms' likelihood of emerging from Chapter 11 bankruptcy. Otherwise, a positive relationship between emerging from bankruptcy and financial benefit from filing, *ceteris paribus*, is taken as evidence of strategic behaviour. Although, this relationship between financial benefit and likelihood of bankruptcy resolution appears to be simple (strategic default is likely to be a function of firms' liquidation costs, and of creditors' coordination and bargaining power as well), Fay *et al.* (2002) and Zhang *et al.* (2015) successfully use similar specification to report strategic behaviour in household bankruptcy filings in the U.S. Besides, our subsequent statistical tests using this specification give results in favour of our hypothesis.

We test the presence of strategic behaviour in bankruptcy emergence by supplementing our bankruptcy emergence model with an additional covariate, $\textit{Financial Benefit}_{it}$, to the model specification in Equation 1. In the analysis of financial benefit from filing, we take a one-year lag of the natural logarithm of *Financial Benefit*$_{i,t}$; that is, ln(*Financial Benefit*$_{it-1}$ + 1) (*FB*). In line with Fay *et al.* (2002), we believe FB must be positive as a company would not file for bankruptcy if its assets exceeded the amount of liabilities. We introduce the strategic behaviour in the Probit regression specification of bankruptcy emergence as follows:

$$(3) \qquad EMERGE_i = f(\upsilon FB + \gamma F_{it} + \delta J_{it} + \phi C_{it} + \eta G_{it} + \varphi M_{it} + u > 0)$$

and report the results in Table 8. To our surprise, we find a positive coefficient of financial benefit indicating that the likelihood of emerging from Chapter 11 bankruptcy increases with increasing financial benefit. This result is similar to Fay *et al.* (2002) and Zhang *et al.* (2015), who report positive relationship between financial benefit and household bankruptcy filing decision. It also resonates with the finding of Adler *et al.* (2013), that in anticipation of bankruptcy, firms tend increase their level of leverage.

Thus, the possibility of any strategic behaviour in bankruptcy resolution cannot be ignored. Additionally, since FB is just significant at the 5% level with a p-value of 0.05 and its inclusion renders TATL insignificant, we re-estimate the model excluding TATL (see columns 4 and 5 in Table 6) as the primary objective of this study is to explore the role of financial benefits in explaining firms' likelihood of emerging from Chapter 11 bankruptcy. Exclusion of TATL makes FB significant at the 1% level with marginal increment in its magnitude (0.1155). Additionally, this does not affect Pseudo R^2 or AUROC significantly, thus our subsequent analysis is based on the model reported in column 4 of Table 6.

[Insert Table 6 Here]

However, this simple empirical relationship between bankruptcy emergence and FB presented in Equation (3) does not consider more realistic relationships among financial benefit, adverse events, and strategic behaviour (Zhang *et al.* 2015). For example, financial benefit from bankruptcy filing may go up due to adverse events, regardless of whether a firm is trying to abuse bankruptcy law or not. That is, financial benefit goes up when a firm consciously increases debts before filing, consistent with strategic behaviour; and it also goes up, when in financial difficulties it uses debt to pay for expenses, consistent with nonstrategic behaviour. Moreover, a nonstrategic firm may appear strategic to analysts, if it rolls over debt as long as there is hope of repaying it. This leads to higher measured financial benefit before filing, despite no intention to abuse bankruptcy law. In other words, financial benefit is affected by both strategic and nonstrategic behaviour, and a positive coefficient on financial benefit alone is insufficient to distinguish between the two behaviours.

Our subsequent test (employ the empirical design suggested by Zhang *et al.* (2015) in context of household bankruptcy) partially disentangles the role of financial benefit, adverse events, and strategic behaviour: it allows for a positive relationship between bankruptcy emergence and financial benefit for both strategic and nonstrategic firms, and still may distinguish between the two. However, this test cannot distinguish between strategic firms, and non-strategic firms who may appear strategic due to a non-strategic run-up of debt before filing.

The existing literature does not provide a clear definition of what constitutes a strategic bankruptcy resolution. However, following the line of reasoning provided by Fay *et al.* (2002) and Zhang *et al.* (2015) in context of household bankruptcy, it is reasonable to define it as the conscious decision of a firm to benefit from the bankruptcy laws at the expense of losses to its creditors. In this context, strategic behaviour may be considered as a two-step decision making process. In the first step, the firm receives adverse noisy signal(s) or shock(s) of experiencing bankruptcy in the near future. Based upon this, the firm evaluates its likelihood of emerging from bankruptcy in the case of Chapter 11 filing, and updates its debt level to maximise its gain from any subsequent bankruptcy filing. Thus, a strategic firm is one which, in the first step, chooses its debt level after conditioning on the signal(s). In other words, a strategic firm is rational and takes decisions to maximise its benefit. On the other hand, a non-strategic firm chooses debt level without conditioning on the signal; it plans to repay its debt in the absence of any adverse event(s).

Consistent with this view, we may distinguish between strategic and non-strategic behaviour in bankruptcy resolution by testing whether firms choose their debt level in the light of pre-evaluated likelihood of emerging from bankruptcy (after realising adverse noise/shocks), or not. Strategic behaviour constitutes a joint decision, otherwise it is considered a non-strategic behaviour. If the strategic behaviour hypothesis is true, *ceteris paribus*, the coefficients of FB should be positive and significant while the adverse event/shock variables should not be significant. If the non-strategic behaviour hypothesis is true, then adverse event variables should be positive and significant while the coefficient of FB should be insignificant.

Thus, before we proceed, we need to define a variable that effectively captures adverse events or deteriorating financial health of a firm. We proxy this with the celebrated Z-Score proposed by Altman (1968) estimated as follows (see Altman *et al.* (2017) for updated and additional discussion on the relevance of Z-Score):

$$Z\text{-}Score_{it} = 1.2\frac{WC_{it}}{TA_{it}} + 1.4\frac{RE_{it}}{TA_{it}} + 3.3\frac{EBIT_{it}}{TA_{it}} + 0.6\frac{E_{it}}{D_{it}} + 0.999\frac{S_{it}}{TA_{it}} \quad (4)$$

where WC_{it} is the working capital of firm i in the year t, RE_{it} is retained earnings, $EBIT_{it}$ is earnings before interest and taxes, E_{it} is the market value of equity, D_{it} is total liabilities, S_{it} is sales and TA_{it} is total assets. This appears perfectly reasonable as higher values of a firm's working capital, retained earnings, earnings, market value and sales are signs of growth and prosperity. The higher the value of Z-Score, the better is the financial health of a firm and vice-versa. Thus, there exists a negative relationship between firms' likelihood of entering financial distress or bankruptcy and Z-Score. Similarly, among the firms which filed for Chapter11 bankruptcy, a firm with a lower value of Z-Score must find emerging from bankruptcy more difficult than one with a higher value of Z-Score.

Thus, intuitively, there should be a positive relationship between Z-Score and firms' likelihood of emerging from bankruptcy. However, regression estimates reported in Table 7 state otherwise. Although Z-Score is highly significant in explaining firms' likelihood of emerging from bankruptcy from one up to five years in advance, the negative coefficients appear to be counterintuitive. This may be possible if firms strategically update their leverage level upward upon receiving an adverse signal in the form of a lower Z-Score (a value below 1.81 signals financial distress), and simultaneously show optimism toward successful bankruptcy resolution in the event of any future bankruptcy filing.

[Insert Table 7 Here]

Coming back to our test of strategic behaviour hypothesis in bankruptcy resolution, we explore strategic and non-strategic behaviour by running a Probit regression of firms emerging from bankruptcy as a function of their FB from filing, firm characteristics, and adverse events (proxied by Z-Score) experienced in the previous year(s). Multivariate regression estimates are reported in Table 8. Columns 2 through to 5 report multivariate regression models for different lags (in years) of Z-Score (lag 1 through to 5). Except for Models 1 and 5, the test results confirm the presence of strategic behaviour in bankruptcy resolution. Coefficients of financial benefit are positive and significant for Models 2, 3 and 4, while coefficients of Z-Score are insignificant.

[Insert Table 8 Here]

However, this simple empirical relationship between bankruptcy resolution and financial benefit conflate more realistic relationships between financial benefit, adverse events, and strategic behaviour. To disentangle some of these relationships, we subsequently test the endogeneity of financial benefit in a more general model in which financial benefit and bankruptcy emergence are allowed to be determined jointly. It is reasonable to believe that a firm's attitude toward debt (and thus financial benefit), which is unobserved, determines both how they accumulate debt and whether or not they emerge if they file for bankruptcy.

1.2. Endogeneity of FB and Bankruptcy Emergence

Following the empirical design suggested by Zhang *et al.* (2015), we test for endogeneity of FB and bankruptcy resolution likelihood by using Z-Score as an instrumental variable. The rationale behind this choice is that, companies' attitude toward financial distress (and thus financial benefit), which is unobserved, determines both their inability to meet their financial obligations toward creditors and their ability to emerge from bankruptcy. Companies behaving strategically determine their debts in order to maximise the financial benefit they can obtain in the bankruptcy resolution process. We expect that companies undertaking these strategies have a higher likelihood of emergence from bankruptcy. Testing this hypothesis corresponds to testing whether FB is endogenous. In this model, adverse events (Z-score at different lags) no longer directly impacts a firm's bankruptcy resolution likelihood. It serves as an instrumental variable that directly affects financial benefit, FB (expressed as $\ln(FB_{it-1})$). As adverse events are exogenous to companies' likelihood of emerging from Chapter 11, it operates more as a shock to firms.

One might question the rational behind our choice of Z-score as an instrumental variable. As we know, any random adverse event to a firm will subsequently affect (adversely) one or more factors of Z-score (i.e. working capital, retained earnings, earnings, market value or sales), which in turn the will affect the Z-score. Thus, Z-score in a way is an aggregate measure that captures the effects of multiple adverse random events a firm faces. We agree that this might not be a perfect instrument for FB, however subsequent test results does not disapprove our choice either.

Indeed, drops in Z-score lead companies to lose credibility which, in turn, leads to reduced access to finance and external credit. Hence, this generates exogeneous shocks. The endogeneity of FB can be detected when error terms in the structural equation and the reduced-form equation for the endogenous variable are correlated, estimated by the parameter Ω in Table 9. For each model, we perform a Walt test of exogeneity to check for the endogeneity of FB, where the null hypothesis is that the covariance between the errors of the structural equation and those of the reduced-form are uncorrelated, $\Omega = 0$. Rejecting the null indicates the presence of endogeneity for the conditions. Since a limitation of this Probit specification with a maximum likelihood estimator is that it is not possible to perform the overidentification test for the instrumental variable, we use Newey's two-step estimator to perform the overidentification and weak instrument tests. Table 9 reports multivariate Probit models with endogenous regressors.

[Insert Table 9 Here]

The coefficient of FB for respective models is highly significant (except IVModel 5) and shows a dramatic increase in magnitude compared to models reported in Table 8, indicating the pivotal role of FB in companies' emergence. The coefficient of FB is maximum (0.3494) when only Z-score with one-year lag is used (IVModel 1), and shows gradual decline in subsequent models with the incorporation of Z-Score with an increasing number of lags. In each specification, the remaining variables capture firm, case and geographic characteristics shown in previous analyses. The estimated correlation parameter Ω is statistically not significant from zero only in the model that includes Z-score from 1-year lag to 5-year lag (IVModel 5). This is consistent with the presence of nonstrategic behaviour. Conversely, all the other models, including a set of instrumental variables with different combinations of Z-score ranging from 1-year lag to 4-year lag, show values of Ω are statistically significant from zero. The test results that are consistent with non-strategic behaviour rule out significant strategic behaviour; in contrast, the results indicating the presence of endogeneity cannot distinguish between strategic and nonstrategic behaviour, as a behaviour may appear strategic but it can be due to non-strategic reasons as well. We interpret our results as an indication that, in the presence of (repeated) adverse events, companies may start acting strategically from 1 up to 4 years before filing for bankruptcy.

As a common practice to verify instrumental validity in our IV Probit models, we use the test of overidentifying restrictions called Amemiya-Lee-Newey Minimum Chi-square. It tests if the instruments are uncorrelated with the error term. In our models, we fail to reject the null hypothesis of orthogonality of the set of instruments with a conventional error of 1%. This confirms the validity of the instruments we used. Moreover, we compute weak-instrument-robust tests of the coefficients on the endogenous regressors in IV Probit estimations (Finlay *et al.* 2014). In an exactly-identified model with one instrument (IVModels 1), the tests reported are the Anderson-Rubin (AR) test statistic and Wald Chi2. When the IV model is overidentified, we conduct the conditional likelihood ratio (CLR) test, the Lagrange multiplier K test, the J overidentification test and Walt Chi-square test (Finlay *et al*. 2014). The results of the CLR, K and J tests corroborate the goodness of the models. In our cases, the AR test statistic indicates that the parameters of the endogenous regressors are jointly significant in all the models with the exception of the IVModel5.

2. Conclusion

This study contributes to the corporate bankruptcy literature by exploring the relative importance of a comprehensive set of predictors (along with firm, judicial, case and geographic and macroeconomic characteristics) in explaining firms' likelihood of emerging from Chapter 11 bankruptcy. Subsequently, we investigate the possibility of any strategic behaviour in firms' likelihood of undergoing successful bankruptcy resolution, and whether this strategic behaviour is endogenous to firms' experience of past adverse event(s).

We identify eight factors that best explain a firm's likelihood of emerging from Chapter 11 bankruptcy with a within-sample classification accuracy of about 94%. Our results indicate that firm characteristics, such as total assets and operation in retail sectors, have a negative and statistically significant impact on firms' emergence likelihood. None of the judicial and macroeconomic predictors seems to play a critical role in predicting companies' emergence likelihood. Covariates capturing case characteristics show mixed impact. The replacement of the CEO after filing for Chapter 11, the presence of a pre-packed or pre-negotiated bankruptcy, and a high ratio of total DIP loan received to total assets before bankruptcy filing have a positive effect on a company's emergence. Conversely, the intention to sell the business and the length of the bankruptcy case dramatically increase the risk of failed bankruptcy resolution. Among geographical factors, the location of the court to which the case is assigned is pivotal in enabling companies' emergence. Filing in debtor-friendly districts (e.g. Delaware or New York) increases the probability of companies' emergence. The implications of this result can have different implications according to the type of stakeholder. While managers and employees can benefit from debtor-friendly practices, increasing the possibility of surviving even in cases in which chances of success are limited (Boettcher et al., 2014) this can bring negative externalities to communities, suppliers and customers (e.g. increasing refiling rates or lowering sales growth).

In order to design policies that can address bankruptcy in a sustainable way, it is critical to understand whether companies filing for Chapter 11 bankruptcy protection do so to gain any strategic advantage, or not. In this study we report significant strategic behaviour among Chapter 11 filing firms. The presence of financial benefit from filing increases firms' likelihood of emerging from bankruptcy. Subsequent analysis of endogeneity or exogeneity of financial benefit and companies' emergence likelihood suggest the presence of strategic behaviour up to four years before filing for Chapter 11bankruptcy. Companies may start acting strategically from one up to four years before filing for bankruptcy in the presence of (repeated) adverse events or financial distress. In the light of this result, policy makers may find it appropriate to amend existing bankruptcy laws to discourage such behaviour, or tighten up access to bankruptcy courts and make bankruptcy more expensive, by: i) restricting access to particular types of bankruptcy provisions; ii) lowering exemptions; iii) diverting more debtors to longer repayment plans; iv) requiring debt management programs outside bankruptcy, etc.

Previous studies show that signals from key external stakeholders contribute to predict the emergence of bankrupt firms by evaluating bankrupt firms' characteristics more effectively as well as reducing the ambiguity in interpreting firms' restructuring signals (Xia et al., 2016). Future research on strategic bankruptcy could benefit from including key external stakeholders (such as alliance partners, institutional investors, and securities analysts) in evaluating companies' turnaround likelihood. Moreover, building on James (2016), future studies should focus on exploring the nature of these benefits in an examination of post-bankruptcy performance.

Bibliography

Adler, B.E., Capkun, V., and Weiss, L.A., 2013. Value destruction in the new era of Chapter 11. *The Journal of Law, Economics, and Organization*, 29 (2), 461–483.

Akerlof, G.A., Romer, P.M., Hall, R.E., and Mankiw, N.G., 1993. Looting: The economic underworld of bankruptcy for profit. *Brookings Papers on Economic Activity*, 1993 (2), 1–73.

Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23 (4), 589–609.

Altman, E.I., Iwanicz-Drozdowska, M., Laitinen, E.K., and Suvas, A., 2017. Financial Distress Prediction in an International Context: A Review and Empirical Analysis of Altman's Z-Score Model. *Journal of International Financial Management & Accounting*, 28 (2), 131–171.

Aysun, U., 2014. Bankruptcy resolution capacity and economic fluctuations. *Journal of Macroeconomics*, 40, 387–399.

Aysun, U., 2015. Duration of bankruptcy proceedings and monetary policy effectiveness. *Journal of Macroeconomics*, 44, 295–302.

Barker III, V.L. and Barr, P.S., 2002. Linking top manager attributions to strategic reorientation in declining firms attempting turnarounds. *Journal of Business Research*, 55 (12), 963–979.

Borenstein, S. and Rose, N.L., 2003. The impact of bankruptcy on airline service levels. *American Economic Review*, 93 (2), 415–419.

Coordes, L.N., 2015. The geography of bankruptcy. *Vanderbilt Law Review*, 68, 381.

Dahiya, S., John, K., Puri, M., and Ramírez, G., 2003. Debtor-in-possession financing and bankruptcy resolution: Empirical evidence. *Journal of Financial Economics*, 69 (1), 259–280.

Denis, D.K. and Rodgers, K.J., 2007. Chapter 11: Duration, Outcome, and Post-Reorganization Performance. *Journal of Financial and Quantitative Analysis*, 42 (01), 101.

Eckbo, B.E. and Thorburn, S.K., 2008. Automatic bankruptcy auctions and fire-sales. *Journal of Financial Economics*, 89 (3), 404–422.

Evans III, J.H., Luo, S., and Nagarajan, N.J., 2013. CEO turnover, financial distress, and contractual innovations. *The Accounting Review*, 89 (3), 959–990.

Evans, J. and Borders, A.L., 2014. Strategically surviving bankruptcy during a global financial crisis: The importance of understanding chapter 15. *Journal of Business Research*, 67 (1), 2738–2742.

Fay, S., Hurst, E., and White, M.J., 2002. The household bankruptcy decision. *American Economic Review*, 92 (3), 706–718.

Finlay, K., Magnusson, L., and Schaffer, M., 2014. WEAKIV10: Stata module to perform weak-instrument-robust tests and confidence intervals for instrumental-variable (IV) estimation of linear, probit and tobit models.

Flynn, D.M. and Farid, M., 1991. The intentional use of Chapter XI: Lingering versus immediate filing. *Strategic Management Journal*, 12 (1), 63–74.

François, P. and Raviv, A., 2017. Heterogeneous beliefs and the choice between private restructuring and formal bankruptcy. *The North American Journal of Economics and Finance*, 41, 156–167.

Franks, J. and Sussman, O., 2005. Financial distress and bank restructuring of small to medium size UK companies. *Review of Finance*, 9 (1), 65–96.

Gilson, S., 2012. Coming through in a crisis: How Chapter 11 and the debt restructuring industry are helping to revive the US economy. *Journal of Applied Corporate Finance*, 24 (4), 23–35.

Gilson, S.C., 2010. *Creating value through corporate restructuring: Case studies in bankruptcies, buyouts, and breakups*. 2nd ed. New Jersy: John Wiley & Sons.

Gupta, J., Barzotto, M., and Khorasgani, A., 2018. Does size matter in predicting SMEs failure? *International Journal of Finance & Economics*.

Gupta, J. and Chaudhry, S.M., 2019. Mind the tail, or risk to fail. *Journal of Business*

Research, 99, 167–185.

Hillegeist, S.A., Keating, E.K., Cram, D.P., and Lundstedt, K.G., 2004. Assessing the probability of bankruptcy. *Review of Accounting Studies*, 9 (1), 5–34.

Hosmer Jr, D.W., Lemeshow, S., and Sturdivant, R.X., 2013. *Applied Logistic Regression*. 3rd ed. New Jersy: John Wiley & Sons.

Koh, S., Durand, R.B., Dai, L., and Chang, M., 2015. Financial distress: Lifecycle and corporate restructuring. *Journal of Corporate Finance*, 33, 19–33.

Li, S., Sougiannis, T., and Wang, I., 2017. *Mandatory IFRS Adoption and the Usefulness of Accounting Information in Predicting Future Earnings and Cash Flows*.

Li, Y., 2013. A nonlinear wealth transfer from shareholders to creditors around Chapter 11 filing. *Journal of Financial Economics*, 107 (1), 183–198.

Long, J.S. and Freese, J., 2014. *Regression models for categorical dependent variables using Stata*. 3rd ed. Texas: Stata press.

LoPucki, L.M. and Doherty, J.W., 2015. Bankruptcy survival. *UCLA Law Review*, 62, 969.

Maskara, P.K. and Miller, L.S., 2018. Do golden parachutes matter? Evidence from firms that ultimately filed for bankruptcy. *The Quarterly Review of Economics and Finance*, 67, 63–78.

Moulton, W.N. and Thomas, H., 1993. Bankruptcy as a deliberate strategy: Theoretical considerations and empirical evidence. *Strategic Management Journal*, 14 (2), 125–135.

Reboul, J. and Toldrà-Simats, A., 2016. The Strategic Behavior of Firms with Debt. *Journal of Financial and Quantitative Analysis*, 51 (5), 1611–1636.

Sarkar, S. and Osiyevskyy, O., 2018. Organizational change and rigidity during crisis: A review of the paradox. *European Management Journal*, 36 (1), 47–58.

Sutton, R.I. and Callahan, A.L., 1987. The stigma of bankruptcy: Spoiled organizational image and its management. *Academy of Management Journalournal*, 30 (3), 405–436.

Teloni, F., 2015. Chapter 11 Duration, Pre-Planned Cases, and Refiling Rates: An Empirical Analysis in the Post BAPCPA Era. *American Bankruptcy Institute Law Review*, 23, 571.

Trahms, C.A., Ndofor, H.A., and Sirmon, D.G., 2013. Organizational decline and turnaround: A review and agenda for future research. *Journal of Management*, 39 (5), 1277–1307.

Yu, K. and He, D., 2018. The choice between bankruptcy liquidation and bankruptcy reorganization: a model and evidence. *Journal of Management Analytics*, 5 (3), 170–197.

Zhang, S., Sabarwal, T., and Gan, L., 2015. Strategic or nonstrategic: The role of financial benefit in bankruptcy. *Economic Inquiry*, 53 (2), 1004–1018.

Zwiebel, J., 1996. Dynamic capital structure under managerial entrenchment. *The American Economic Review*, 86 (5), 1197–1215.

1: Sample Description

Year	Total Number of Filings	Number of Firms Emerged	% of Firms Emerged
(1)	(2)	(3)	(4) = (2/3) ×100
1994	8	4	50.00
1995	6	5	83.33
1996	8	2	25.00
1997	7	5	71.43
1998	18	11	61.11
1999	23	15	65.22
2000	44	25	56.82
2001	53	28	52.83
2002	27	17	62.96
2003	23	17	73.91
2004	14	12	85.71
2005	13	11	84.62
2006	6	6	100.00
2007	6	5	83.33
2008	12	7	58.33
2009	46	34	73.91
2010	6	5	83.33
2011	8	4	50.00
2012	9	5	55.56
2013	14	10	71.42
2014	9	5	55.56
2015	16	9	56.25
2016	23	20	86.97
2017	2	2	100.00
Total	401	264	

Notes: This table reports year-wise distribution of Chapter 11 filings (column 2) and number of firms that emerged (column 3) from Chapter 11 bankruptcy in our sample. Percentage of firms emerging from Chapter 11 in any given year is reported in column 4.

Table 2: Firms' Industrial Classification

Industry Code	SIC Code	Industry
1	< 1000	Agriculture, Forestry, Fishing
2	1000 to < 1500	Mining
3	1500 to < 1800	Construction
4	2000 to < 4000	Manufacturing
5	5000 to < 5200	Wholesale Trade
6	5200 to < 6000	Retail Trade
7	7000 to < 8900	Services

Notes: This table reports Standard Industrial Classification (SIC) of US firms. SIC Code is a four-digit code that represents given industrial sectors.

Table 3: Correlation Matrix

Variable		1	2	3	4	5	6	7	8	9	10	11
CSIZE	1	1.0000										
TATL	2	-0.0196	1.0000									
PEBIT	3	0.1166	-0.0009	1.0000								
EMP	4	0.5099	-0.0313	0.2103	1.0000							
INDUSTRY-M	5	-0.0773	0.0556	-0.0976	0.2881	1.0000						
INDUSTRY-R	6	0.0712	-0.1663	0.1230	0.0601	-0.4114	1.0000					
JEXP	7	0.0540	-0.0814	-0.0058	0.0242	-0.0970	0.0115	1.0000				
JEXPD	8	0.0435	-0.0999	0.0042	0.0426	-0.0489	0.0111	0.8546	1.0000			
AEXP	9	0.3047	-0.0489	-0.0039	0.1738	0.0749	0.0236	0.2575	0.2025	1.0000		
CEOR	10	0.1020	-0.1554	0.1313	0.1514	-0.1369	0.1596	0.0520	0.0445	0.0422	1.0000	
CEODA	11	0.1133	-0.1090	0.0787	0.0754	-0.0408	0.1104	-0.0066	-0.0067	0.0798	0.0761	1.0000
SALEINT	12	-0.1430	0.2496	-0.1211	-0.1264	-0.0039	0.0082	0.1187	0.1096	0.0092	-0.3147	-0.2314
PREAGR	13	-0.0686	-0.1725	0.0741	-0.1166	-0.1609	-0.0141	0.1187	0.0784	0.0742	0.1322	0.0322
DURATION	14	0.2173	-0.0096	0.0294	0.2324	0.1782	0.0720	0.0214	0.0434	0.1441	0.0349	0.1159
CCOM	15	0.0930	0.0313	-0.0555	0.1065	0.1244	0.0641	-0.0278	-0.0088	0.0246	-0.0933	-0.0410
CFILE	16	-0.1129	0.0513	-0.0099	-0.0757	0.0748	-0.0522	-0.5572	-0.5170	-0.2195	-0.0545	-0.1435
HCCTODE	17	-0.0847	0.1448	-0.1390	-0.1699	-0.0229	-0.1454	0.0139	0.0053	-0.0757	-0.1411	-0.1437
BSHOP	18	0.1606	-0.0795	-0.0448	0.0773	-0.0752	-0.0272	0.4836	0.4039	0.2249	0.0229	0.1016
DIPL	19	0.0579	-0.0470	0.0278	-0.0140	-0.0489	0.1413	0.1514	0.1100	0.2488	0.1321	-0.0651
DIPTA	20	0.0020	-0.0849	0.0271	0.0793	0.0478	0.1026	0.1485	0.1404	0.1978	0.1515	0.0163
PRIME1	21	0.0231	0.0876	0.0642	0.1734	0.1328	-0.0702	-0.2476	-0.2005	-0.2628	-0.0799	0.1396
PRIMEF	22	-0.0881	0.0635	0.0292	0.1414	0.2085	-0.1530	-0.2685	-0.1847	-0.3013	0.0279	0.1410
Variable		12	13	14	15	16	17	18	19	20	21	22
SALEINT	12	1.0000										
PREAGR	13	-0.2425	1.0000									
DURATION	14	-0.0444	-0.3857	1.0000								
CCOM	15	0.1734	-0.5231	0.3098	1.0000							
CFILE	16	-0.0258	-0.145	-0.0157	0.1177	1.0000						
HCCTODE	17	0.1356	-0.1103	-0.0730	0.1401	0.1839	1.0000					
BSHOP	18	0.0286	0.1380	-0.0316	-0.0541	-0.6714	0.0105	1.0000				
DIPL	19	0.0180	0.0525	-0.1504	0.0078	-0.0145	-0.0034	0.0646	1.0000			
DIPTA	20	-0.0088	-0.0233	-0.0678	0.0541	-0.0933	0.0088	0.1454	0.7002	1.0000		
PRIME1	21	-0.0656	-0.1713	0.2499	0.1124	0.0653	-0.0076	-0.1246	-0.5441	-0.3566	1.0000	
PRIMEF	22	-0.1587	-0.1416	0.2317	0.0839	0.0594	-0.0519	-0.1250	-0.4697	-0.2580	0.7180	1.0000

Notes: This table reports correlation among the set of covariates estimated over the sample period 1994-2017.

Figure 1: Receiver Operating Characteristic Curve

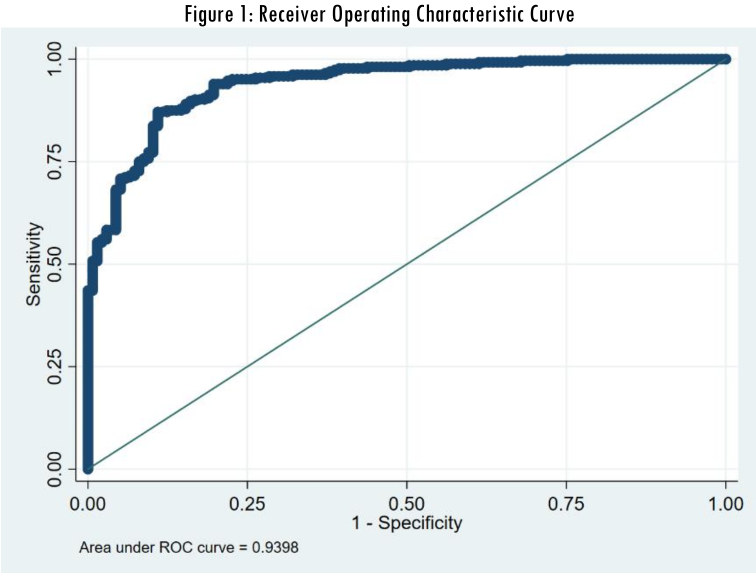

Table 4: Univariate Probit Regression

Variable	Sign	Coefficient	Standard Error	AME in %	Rank of AME
(1)	(2)	(3)	(4)	(5)	(6)
CSIZE	+	0.2219[a]	0.0721	7.98[a]	14
TATL	-	-0.6350[a]	0.1345	-21.77[a]	7
PEBIT	+	0.3462[a]	0.1302	12.52[a]	11
EMP	+	0.0885[b]	0.0423	3.22[b]	20
INDUSTRY-M	+	0.3592[a]	0.1321	12.98[a]	------
INDUSTRY-R	-	-0.6345[a]	0.1726	-22.63[a]	6
JEXP	+	0.1733[a]	0.0598	6.25[a]	16
JEXPD	+	0.3167[b]	0.1397	11.50[b]	13
AEXP	+	0.1990[a]	0.0538	7.10[a]	15
CEOR	+	1.9302[a]	0.1544	44.61[a]	2
CEODA	+	0.4544[a]	0.0823	15.06[a]	10
SALEINT	-	-1.0868[a]	0.1467	-35.15[a]	3
PREAGR	+	0.8725[a]	0.1557	29.80[a]	4
DURATION	-	-0.1068[b]	0.0438	3.87[b]	18
CCOM	-	-0.7716[a]	0.2067	-27.43[a]	5
DIPL	+	0.5707[a]	0.1435	20.24[a]	8
DIPTA	+	2.7448[a]	0.6823	96.89[a]	1
CFILE	-	-0.4305[a]	0.1325	-15.46[a]	9
HCCTODE	-	-0.2522[b]	0.0975	-5.60[a]	17
BSHOP	+	0.3413[b]	0.1416	12.38[b]	12
PRIME1	-	-0.0894[a]	0.0289	-3.22[a]	19
PRIMEF	-	-0.0584[b]	0.0280	-2.12[b]	21

Notes: a (b) [c] significant at the 1% (5%) [10%] level (two-sided test). This table reports univariate Probit regression estimates of respective covariates using EMERGE as the dependent variable. 'Sign' (Column 2) represents expected sign of regression coefficients. Column 3 reports the regression coefficient (β), Column 4 indicates the standard error, Column 5 presents the Average Marginal Effect in percentage, and Column 6 reports the ranking of variables based on the magnitude of their AME.

Table 5: Multivariate Regression Models

Variable	Probit Model			Logit Model		
	Coefficient	Standard Error	AME in %	Coefficient	Standard Error	AME in %
(1)	(2)	(3)	(4)	(5)	(6)	(7)
DIPTA	3.6088[a]	1.1447	58.41[a]	6.5445[a]	2.0980	58.44[a]
CEOR	2.2561[a]	0.2161	36.52[a]	4.0217[a]	0.4233	35.91[a]
SALEINT	-1.0020[a]	0.2622	-16.22[a]	-1.7639[a]	0.3924	-15.75[a]
PREAGR	0.9561[a]	0.2573	15.48[a]	1.7150[a]	0.4583	15.31[a]
INDUSTRY-R	-0.7160[a]	0.2608	-11.59[a]	-1.2932[a]	0.4604	-11.54[a]
TATL	-0.3280[a]	0.1681	-5.31[b]	-0.6438[b]	0.3059	-5.74[b]
BSHOP	0.4417[b]	0.2090	7.15[b]	0.7816[b]	0.3779	6.97[b]
DURATION	-0.1357[b]	0.0664	-2.20[b]	-0.2448[b]	0.1171	-2.18[b]
Model's goodness of fit and classification performance measures						
Log likelihood	-116.5264			-116.4806		
LR Chi2	281.93[a]			282.02[a]		
Pseudo R^2	0.5475			0.5480		
AUROC	0.9398			0.9397		
N = 1	264			264		
N = 0+1	401			401		

Notes: a (b) [c] significant at the 1% (5%) [10%] level (two-sided test). Columns 2 and 5 report regression coefficients (β) of multivariate Probit and Logit models, respectively. Columns 3 and 6 report standard errors of respective coefficients, and Columns 4 and 7 report their Average Marginal Effects in percentage. Models' goodness of fit and classification performance measures are reported in the last six rows. AUROC is Area under the Receiver Operating Characteristic. N = 1 is the number of firms emerging from bankruptcy; whilst N = 0+1 represents the total number of firms that filed for Chapter 11 bankruptcy between 1994 and 2017.

Table 6: Multivariate Probit Models for Strategic Behaviour in Bankruptcy Resolution

Variable	With TATL		Without TATL	
	Coefficient	Standard Error	Coefficient	Standard Error
(1)	(2)	(3)	(4)	(5)
Financial Benefit	0.0959[b]	0.0498	0.1155[a]	0.0465
DIPTA	3.7453[a]	1.1701	3.8622[a]	1.1792
CEOR	2.2687[a]	0.2218	2.2712[a]	0.2219
SALEINT	-0.9790[a]	0.2176	-1.0161[a]	0.2153
PREAGR	0.9475[a]	0.2609	0.9801[a]	0.2601
INDUSTRY-R	-0.6473[b]	0.2659	-0.6618[a]	0.2664
TATL	-0.1878	0.1769	------	------
BSHOP	0.4078[b]	0.2127	0.4151[b]	0.2123
DURATION	-0.1546[b]	0.0685	-0.1558[b]	0.0683
Model's goodness of fit and classification performance measures				
Log likelihood	-114.5213		-115.1855	
LR Chi2	273.98[a]		272.66[a]	
Pseudo R^2	0.5447		0.5420	
AUROC	0.9385		0.9379	
N = 1	260		260	
N = 0+1	393		393	

Notes: a (b) [c] significant at the 1% (5%) [10%] level (two-sided test). Columns 2 and 4 report regression coefficients (β) of multivariate Probit models with and without TATL, respectively. Columns 3 and 5 report standard errors of respective coefficients. Models' goodness of fit and classification performance measures are reported in the last six rows. AUROC is Area under the Receiver Operating Characteristic. N = 1 is the number of firms emerging from bankruptcy; whilst N = 0+1 represents the total number of firms that filed for Chapter 11 bankruptcy between 1994 and 2017.

Table 7: Univariate Probit Estimates for Z-Score

Variable	Coefficient	Standard Error
Z-Score (T-1)	-0.3510[a]	0.0666
Z-Score (T-2)	-0.1410[a]	0.0459
Z-Score (T-3)	-0.1135[a]	0.0401
Z-Score (T-4)	-0.0872[a]	0.0354
Z-Score (T-5)	-0.0958[a]	0.0409

Notes: [a] significant at the [1%] level (two-sided test).

Table 8: Multivariate Probit Models for Strategic Behaviour in Bankruptcy Resolution with Adverse Event (Z-score)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
(1)	(2)	(3)	(4)	(5)	(6)
Financial Benefit	0.0591 (0.0522)	0.1043[b] (0.0487)	0.0947[b] (0.0479)	0.0799[c] (0.0483)	.0605 (.0488)
Z-Score (T-1)	-0.1315[b] (0.0566)				
Z-Score (T-2)		0.0061 (0.0371)			
Z-Score (T-3)			-0.0168 (0.0332)		
Z-Score (T-4)				-0.0297 (0.0284)	
Z-Score (T-5)					-0.0127 (0.0344)
DIPTA	3.5755[a] (1.1567)	3.8981[a] (1.2444)	3.8361[a] (1.2364)	3.6703[a] (1.2491)	3.5198[a] (1.2682)
CEOR	2.2881[a] (0.2229)	2.2587[a] (0.2299)	2.1847[a] (0.2304)	2.1147[a] (0.2330)	2.0699[a] (0.2405)
SALEINT	-0.9980[a] (0.2193)	-0.9947[a] (0.2230)	-1.0440[a] (0.2260)	-1.0078[a] (0.2321)	-0.9826[a] (0.2430)
PREAGR	0.8403[a] (0.2669)	0.9485[a] (0.2713)	0.8896[a] (0.2702)	0.8345[a] (0.2785)	0.9231[a] (0.2981)
INDUSTRY-R	-0.4787[c] (0.2754)	-0.6768[b] (0.2828)	-0.6678[b] (0.2835)	-0.7771[a] (0.3006)	-0.8055[b] (0.3319)
BSHOP	0.4226[b] (0.2168)	0.3782[c] (0.2181)	0.3933[c] (0.2226)	0.4111[c] (0.2282)	0.3066 (0.2377)
DURATION	-0.1599[b] (0.0681)	-0.1523[b] (0.0690)	-0.1508[b] (0.0695)	-0.1266[c] (0.0717)	-0.0926 (0.0739)
Model's goodness of fit and classification performance measures					
Log likelihood	-111.9497	-108.3952	-105.919	-99.8865	-88.8330
LR Chi2	279.13[a]	244.96[a]	230.79[a]	208.35[a]	185.98[a]
Pseudo R^2	0.5549	0.5305	0.5214	0.5105	0.5114
N = 1	260	253	240	228	206
N = 0+1	393	370	353	330	296

Notes: a (b) [c] significant at the 1% (5%) [10%] level (two-sided test). Standard errors are reported in parentheses. Models' goodness of fit measures are reported in the last five rows. N = 1 is the number of firms emerging from bankruptcy; whilst N = 0+1 represents the total number of firms that filed for Chapter 11 bankruptcy between 1994 and 2017.

Table 9: Multivariate Probit Models for Strategic Behaviour in Bankruptcy Resolution with Endogenous Regressors (Z-score)

Variable	IVModel 1	IVModel 2	IVModel 3	IVModel 4	IVModel 5
(1)	(2)	(3)	(4)	(5)	(6)
Correlation (Ω)	-0.6578[a] (0.1692)	-0.5058[a] (0.1996)	-0.5376[b] (0.1947)	-0.3541[c] (0.1757)	-0.2306 (0.2077)
Emergence Equation					
Financial Benefit	0.3494[a] (0.0647)	0.2804[a] (0.0781)	0.2868[a] (0.0763)	0.2103[a] (0.0737)	0.1369 (0.0847)
DIPTA	2.4253[a] (1.1183)	2.9378[b] (1.2208)	2.8863[b] (1.2021)	3.2048[a] (1.2278)	3.2968[a] (1.2763)
CEOR	1.5862[a] (0.4044)	1.8473[a] (.3593)	1.7760[a] (0.3524)	1.9243[a] (0.2642)	1.9734[a] (0.2670)
SALEINT	-0.6011[b] (0.2604)	-0.7386[a] (0.2576)	-0.7415[a] (0.2628)	-0.8303[a] (0.2484)	-0.8862[a] (0.2602)
PREAGR	0.5363[c] (0.2868)	0.6532[b] (0.2923)	0.6122[b] (0.2861)	0.7186[a] (0.2808)	0.8477[a] (0.3087)
INDUSTRY-R	-0.1764 (0.2832)	-0.3161 (0.3082)	-0.3068 (0.3141)	0.5761[c] (0.3238)	-0.7200[b] (0.3545)
BSHOP	0.1773 (0.2023)	0.2290 (0.2156)	0.2060 (0.2174)	0.2743 (0.2743)	0.2621 (0.2383)
DURATION	-0.1472[b] (0.0592)	-0.1551[b] (0.0631)	-0.1548[b] (0.0624)	-0.1358[b] (0.0685)	-0.0985 (0.0727)
Financial Benefit Equation					
Z-Score (T-1)	-.3250[a] (.0452)	-0.3943[a] (0.0606)	-0.3855[a] (0.0626)	-0.4322[a] (0.0671)	-0.4836[a] (0.0776)
Z-Score (T-2)		-0.0266 (0.0515)	0.0433 (0.0667)	-0.0665 (0.0749)	-0.1493[c] (0.0879)
Z-Score (T-3)			-0.0883[c] (0.0523)	-0.0581 (0.0704)	0.0336 (0.0907)
Z-Score (T-4)				-0.0945[b] (0.0437)	-0.2212[b] (0.0901)
Z-Score (T-5)					0.1269[b] (0.0595)
SD of error terms	2.1577 (0.0769)	2.1551 (0.0792)	2.1558 (0.0812)	2.0708 (0.0810)	2.0842 (0.0859)
Model's goodness of fit measures					
Log likelihood	-971.8358	-915.2914	-873.3631	-800.4516	-721.1457
Wald Chi2	162.27[a]	125.84[a]	125.03[a]	103.38[a]	90.48[a]
Wald Exogeneity test Chi2	6.99[a]	4.31[b]	4.81[b]	3.39[c]	1.15
N = 1	260	253	240	228	206
N = 0+1	393	370	353	330	296
Overidentifying test Chi2	0.000	1.718	1.520	2.767	4.899
Weak instrument tests					
CLR		5.1500[b]	5.4800[b]	4.8000[a]	1.5800
K		4.9900[b]	5.3300[b]	4.6400[a]	1.4900
J		1.9400	1.7600	2.9300	5.0500
AR chi2	8.5000[a]	6.9300[b]	7.0900[c]	7.5800	6.5400
Wald chi2	7.5300[a]	4.8200[b]	5.0900[b]	4.5300[a]	1.5100

Notes: a (b) [c] significant at the 1% (5%) [10%] level (two-sided test). Standard errors are reported in parentheses. Models' goodness of fit measures are reported in the last twelve rows. N = 1 is the number of firms emerging from bankruptcy; whilst N = 0+1 represents the total number of firms that filed for Chapter 11 bankruptcy between 1994 and 2017. Overidentifying test Chi2 is for Amemiya-Lee-Newey test of overidentifying restrictions. Weak instrument tests: Conditional Likelihood Ratio (CLR) test, Lagrange multiplier K test, the J overidentification test, the Anderson-Rubin (AR) test statistic and Wald Chi-square test (Finlay et al., 2014).

Appendix

Table A1: Variable Description

No.	Characteristic Group	Variable	Description	BRD Name
1	Firm	CSIZE	The debtor's size, measured as the log of the debtor's total assets in current dollars, as reported on the debtor's last annual report before bankruptcy.	AssetsCurrDollar
2	Firm	TATL	Ratio of Total Assets to Total Liabilities before filing bankruptcy.	AssetsBefore/LiabBefore
3	Firm	PEBIT	Dummy variable, which equals 1 for EBIT>0 and 0 otherwise.	EbitBefore
4	Firm	EMP	Natural logarithm of the number of persons employed by the debtor as of the last 10-K before filing.	EmplBefore
5	Firm	INDUSTRY	This is a factor variable built using Standard Industrial Classification Code of firms. "0" represents the reference category, while "4" and "6" represent manufacturing and retail firms respectively.	SICDivision
6	Judicial	JEXP	Natural logarithm of the number of cases the judge has completed at confirmation of the instant case.	JudgeDisposition
7	Judicial	JEXPD	Dummy variable equalling 1 if the Judge has completed more than 5 cases; 0 otherwise	JudgeDisposition
8	Judicial	AEXP	Natural logarithm of the number of cases the lead counsel (who represented the DIP in filing of the bankruptcy case) or the Attorney has handled before this case.	DipAtty
9	Case	CEOR	Dummy variable equalling 1 if the CEO at filing was replaced after the date on which the debtor's CEO at filing ceased to be the CEO by another CEO or another manager; and 0 otherwise.	CeoReplaced
10	Case	CEODA	Number of days (expressed in years) in which the CEO filing bankruptcy ceased to be the CEO from the day in which the bankruptcy case was filed.	(DateCeoEnd - DateFiled)/365
11	Case	SALEINT	Dummy variable equalling 1 if - at the time of filing - the debtor publicly indicated an intention to sell or liquidate all or substantially all of its assets (including maybe cases).	SaleIntended
12	Case	PREAGR	Dummy variable equalling 1 for a prepackaged or prenegotiated case, and 0 for a free fall case.	Prepackaged
13	Case	DURATION	Number of years between the filing date (DateFiled) and the confirmation date of a Chapter 11 re-organisation (DateConfirm) or the date on which the Chapter 11 case was converted to Chapter 7 or dismissed (DateConvDismiss), whichever is applicable.	DaysIn/365
14	Case	CCOM	Dummy variable equalling 1 if the U.S. Trustee appointed a creditors' committee to represent the unsecured creditors prior to case disposition; 0 otherwise.	CommCred
15	Case	DIPL	Dummy variable equalling 1 if the court approved DIP borrowing outside the ordinary course of business; 0 otherwise	DipLoan1Total
16	Case	DIPTA	Ratio of total DIP loan received to total assets before bankruptcy filing.	(DipLoan1Total+DipLoan2Total)/ AssetsBefore
17	Geographic	CFILE	CityFiled, categorised as Wilmington (DE, 1), New York (NY, 2) or all other cities (OT, 3).	DENYOther
18	Geographic	HCCTODE	Natural logarithm of the number of miles from the debtor's bankruptcy court to which the debtor's case has been assigned (HeadCourtCity) to Wilmington, DE, measured as the crow flies.	HeadCourtCityToDE
19	Geographic	BSHOP	Dummy variable equalling 1 if the city in which the case was filed does not match the location of the bankruptcy court to which the debtor's case has been assigned; 0 otherwise.	Shop
20	Economic Environment	PRIME1	Prime rate of interest one year before case filing.	Prime1YearBefFile
21	Economic Environment	PRIMEF	Prime rate of interest on the bankruptcy filing date.	PrimeFiling

Table A2: Descriptive Statistics

Variable	Statistics	Emerging	Non-emerging	Variable	Statistics	Emerging	Non-emerging
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CSIZE				SALEINT			
	Mean	7.0175	6.7076		Mean	0.1515	0.5109
	Median	6.7939	6.4877		Median	0.0000	1.0000
	SD	1.0126	0.8286		SD	0.3592	0.5017
	Minimum	5.5334	5.6560		Minimum	0.0000	0.0000
	Maximum	11.5454	9.2345		Maximum	1.0000	1.0000
TATL				PREAGR			
	Mean	1.0944	1.5509		Mean	0.4129	0.1387
	Median	1.0443	1.2404		Median	0.0000	0.0000
	SD	0.4450	1.3164		SD	0.4933	0.3469
	Minimum	0.1761	0.4365		Minimum	0.0000	0.0000
	Maximum	3.9286	10.1751		Maximum	1.0000	1.0000
PEBIT				DURATION			
	Mean	0.5341	0.3942		Mean	1.2211	1.6002
	Median	1.0000	0.0000		Median	0.8370	1.1644
	SD	0.4998	0.4905		SD	1.4086	1.5294
	Minimum	0.0000	0.0000		Minimum	0.0849	0.0356
	Maximum	1.0000	1.0000		Maximum	10.8356	12.2411
EMP				CCOM			
	Mean	8.2275	7.8912		Mean	0.7916	0.9343
	Median	8.2990	7.8917		Median	1.0000	1.0000
	SD	1.5650	1.4505		SD	0.4068	0.2487
	Minimum	0.0000	3.7136		Minimum	0.0000	0.0000
	Maximum	12.4372	11.2010		Maximum	1.0000	1.0000
INDDUSTRY-M				DIPL			
	Mean	0.4848	0.3431		Mean	0.4091	0.2117
	Median	0.0000	0.0000		Median	0.0000	0.0000
	SD	0.5007	0.4765		SD	0.4926	0.4100
	Minimum	0.0000	0.0000		Minimum	0.0000	0.0000
	Maximum	1.0000	1.0000		Maximum	1.0000	1.0000
INDDUSTRY-R				DIPTA			
	Mean	0.1098	0.2555		Mean	0.0824	0.0271
	Median	0.0000	0.0000		Median	0.0000	0.0000
	SD	0.3133	0.4377		SD	0.1455	0.0800
	Minimum	0.0000	0.0000		Minimum	0.0000	0.0000
	Maximum	1.0000	1.0000		Maximum	0.7359	0.5235
JEXP				CFILE			
	Mean	1.3726	0.2628		Mean	0.3220	0.4891
	Median	1.3863	0.6931		Median	0.0000	0.0000
	SD	1.1345	1.0383		SD	0.4681	0.5017
	Minimum	0.0000	0.0000		Minimum	0.0000	0.0000
	Maximum	3.6889	3.5835		Maximum	1.0000	1.0000
JEXPD				HCCTODE			
	Mean	0.3750	0.2628		Mean	6.1884	6.5161
	Median	0.0000	0.0000		Median	6.4816	6.6758
	SD	0.4850	0.4418		SD	1.2218	1.0824
	Minimum	0.0000	0.0000		Minimum	0.0000	3.8501
	Maximum	1.0000	1.0000		Maximum	7.8192	7.8296
AEXP				BSHOP			
	Mean	1.5942	1.1115		Mean	0.7576	0.6423
	Median	1.3863	0.6931		Median	1.0000	1.0000
	SD	1.2470	1.1696		SD	0.4294	0.4811
	Minimum	0.0000	0.0000		Minimum	0.0000	0.0000
	Maximum	3.8918	3.8286		Maximum	1.0000	1.0000
CEOR				PRIME1			
	Mean	0.8523	0.1825		Mean	6.0786	6.8157
	Median	1.0000	0.0000		Median	6.0000	7.7500
	SD	0.3555	0.3877		SD	2.2124	2.2760

	Minimum	0.0000	0.0000		Minimum	3.2500	3.2500
	Maximum	1.0000	1.0000		Maximum	9.5000	9.5000
CEODA				PRIMEF			
	Mean	1.7595	0.6594		Mean	6.0786	6.0292
	Median	0.9671	0.4575		Median	6.0000	6.0000
	SD	2.0603	0.6879		SD	2.2124	2.3321
	Minimum	0.0000	-0.0192		Minimum	3.2500	3.2500
	Maximum	12.4849	4.0356		Maximum	9.5000	9.5000

Notes: Columns 1 and 5 list the main variables that are described in Table A1. Columns 2 and 6 indicate the names of descriptive measures. Columns 3 and 7 report descriptive measures for companies that have emerged from Chapter 11 bankruptcy, while Columns 4 and 8 present similar information for companies that have failed to emerge.