Article:

Gupta, Jairaj, Barzotto, Mariachiara and de Moura, André Aroldo Freitas (2024) Bankruptcy Resolution : Misery or Strategy. Abacus. abac.12311. ISSN 1467-6281

https://doi.org/10.1111/abac.12311

ABACUS A Journal of Accounting, Finance and Business Studies

THE UNIVERSITY OF SYDNEY

ABACUS, 2024 doi: 10.1111/abac.12311

JAIRAJ GUPTA, MARIACHIARA BARZOTTO, AND ANDRÉ AROLDO FREITAS DE MOURA

Bankruptcy Resolution: Misery or Strategy

Contrary to conventional wisdom, this study reports a positive relationship between large US firms' leverage levels and their likelihood of emerging from Chapter 11 bankruptcy. In anticipation of a favourable court outcome, which allows them to emerge from bankruptcy with reduced debt, firms tend to increase their leverage levels in the years preceding the bankruptcy filing year. This suggests strategic abuse of bankruptcy courts and creditors. Test results suggest that firms start acting strategically up to four years before filing for bankruptcy so that they can emerge with a reduced debt burden at the cost of creditors. Additionally, our study also contributes to the corporate bankruptcy literature by exploring a set of factors (related to the firm, judicial, case, geographic, and macroeconomic characteristics) explaining the likelihood of firms emerging from bankruptcy, and proposing a parsimonious multivariate model that best predicts the likelihood of surviving Chapter 11 bankruptcy.

Key words: Bankruptcy resolution; Chapter 11 bankruptcy; Financial benefit; Financial distress; Strategic behaviour.

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 be forced into liquidation. Thus, the immediate concern for 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 more than six decades exists on the prediction of bankruptcy likelihood (Altman, 1968; Hillegeist *et al*., 2004; Gupta and Chaudhry, 2019, etc.), the literature pertaining to bankruptcy resolution is relatively small.

Jairaj Gupta (jairaj.gupta@york.ac.uk) is with the University of York. Mariachiara Barzotto is with the University of Bath. André Aroldo Freitas De Moura is with the Fundação Getulio Vargas (FGV) – EAESP.

Jairaj Gupta and Mariachiara Barzotto gratefully acknowledge research support from the UK Department for Business, Energy and Industrial Strategy, through The British Academy Small Research Grant (SRG1819\190953). The authors are grateful to *Abacus* editors and anonymous reviewers, as well as conference participants of the American Economic Association Annual Meeting (San Diego, 2020), 94th Annual Conference of the Western Economic Association International (San Francisco, 2019), and the India Finance Conference 2018 (Kolkata, 2018) for their insightful comments and suggestions that improved this paper significantly.

This study aims to contribute to the literature on organizational decline, corporate turnarounds (Barker III and Barr, 2002), risk-shifting (Aretz *et al*., 2019; Gilje, 2016), and finance theories of corporate restructuring (Koh *et al*., 2015) by addressing this gap in the literature. In the first part of this study, we examine 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 could guide various stakeholders (such as bankruptcy courts, lenders, and traders of distressed firms) in making informed decisions.

Moreover, the major goal of any bankruptcy law is to prevent abusive or fraudulent use of the bankruptcy system, or, in other words, strategic abuse 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 they have exhausted the remaining available options (Sutton and Callahan, 1987). However, Delaney (1999) challenges these assertions by conceiving bankruptcy as a strategic weapon for corporations to use their power in order to avoid current financial burdens and shift future financial risk toward more vulnerable groups in 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 the context of household bankruptcy, considering strategic behaviour to be a company's conscious decision to benefit from bankruptcy law could be a reasonable exposition.

In this context, strategic behaviour may be considered a two-step decision-making process. In the first step, the firm receives noisy adverse signal(s) or shock(s) of experiencing bankruptcy in the near future. Based upon this anticipation, the firm then evaluates its likelihood of emerging from bankruptcy in the case of Chapter 11 filing and updates its debt level to maximize its gain from any subsequent bankruptcy filing. The 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 that, 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 maximize 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).

An emerging, but still scant, stream of research is consistent 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 could be highly desirable in the presence of a higher likelihood of bankruptcy emergence, that is, 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, 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 Bankruptcy Research Database (BRD),[1] and relevant financial data from the Compustat database. The empirical analysis is based upon a relatively long analysis period of 26 years, which includes 574 Chapter 11 bankruptcy filings and 398 successful bankruptcy reorganizations of non-financial firms between 1994 and 2019. 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).

Lopucki and Doherty (2015) explore the information content of a comprehensive set of covariates (about 70) in explaining bankruptcy resolution of large firms in the US 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 selecting the multivariate model with the highest pseudo R-squared and statistical significance of covariates at 10 % or lower levels. Although we build upon their work, we significantly differ from them in several respects: (1) unlike them, 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); (2) unlike them, we report our proposed multivariate model's classification performance, which is excellent at about 95% for within-sample and 91% for hold-out sample; (3) arguably our model is numerically more stable and robust, as their model includes 11 covariates with unreported classification performance, and our parsimonious model gives a within-sample classification accuracy of about 95% with 10 covariates; (4) the pseudo R-squared of our model is about 0.60, which is about 34.2% higher than their model; (5) 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; and, finally, (6) the most significant difference is that we explore whether financial benefits play any strategic role in firms' likelihood of emerging from Chapter 11 bankruptcy.

Empirical results indicate that, amongst firm characteristics, the ratio of total liabilities to total assets has a positive impact on a firm's emergence likelihood,

[1] UCLA-LoPucki Bankruptcy 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 is updated monthly. Further details can be found at: http://lopucki.law.ucla.edu. Amongst others, this dataset has been used by Xia *et al.* (2016).

whilst operating in the retail industry has a negative impact. 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 increases the likelihood of emergence. In contrast, announcing the intention to sell the business upon the bankruptcy filing and the appointment of a creditors committee of unsecured creditors increases the risk of unsuccessful resolution. We also find that the time span between the date on which the CEO filed the bankruptcy case and when they ceased to be the CEO bears a positive relation to emergence. Lastly, our findings suggest that the judge's experience is positively related to emergence, whereas the prime rate of interest on the bankruptcy filing date is negatively related.

Moreover, we make an additional significant contribution to the corporate bankruptcy literature by analysing the role of financial benefits in bankruptcy resolution as a proxy for strategic corporate behaviour in Chapter 11 filings. The empirical design to test this hypothesis is motivated from a study on household bankruptcy decisions by Fay *et al.* (2002). The authors report that households are more likely to file for bankruptcy when their financial benefit from filing is higher. Therefore, we measure the financial benefit of a firm as the positive difference between its total liabilities and total assets, otherwise zero. In this approach, a positive relation between bankruptcy emergence and financial benefit from filing, *ceteris paribus*, is taken as evidence of strategic behaviour; and a positive relation between unsuccessful bankruptcy resolution and adverse events (such as prolonged poor financial health) is taken as evidence of non-strategic behaviour. Multivariate probit estimates show the coefficient of financial benefit is *positive* and highly significant in explaining successful bankruptcy resolution. We also find that firms increase their borrowings up to four years prior to the bankruptcy filing year. Thus, overall, this supports the presence of strategic behaviour and its positive association with a firm's emergence likelihood.

However, this simple empirical relation between bankruptcy emergence and financial benefit does not consider more realistic relations among financial benefits, adverse events, and strategic behaviour (see Zhang *et al.* (2015) for a similar discussion in the context of household bankruptcy). For example, financial benefits 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, the 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 non-strategic behaviour. Moreover, a non-strategic firm may appear strategic to analysts when it rolls over debt if there is the hope of repaying it. This leads to higher measured financial benefits before filing, despite no intention to abuse bankruptcy laws or creditors. In other words, the financial benefit is affected by both strategic and non-strategic behaviours, and a positive coefficient on financial benefit alone is insufficient to distinguish between the two behaviours.

Thus, the subsequent test (employing the empirical design suggested by Zhang *et al*. (2015) in the context of household bankruptcy) partially disentangles the role of financial benefits, adverse events, and strategic behaviour. It allows for a positive relation between bankruptcy emergence and financial benefit for both strategic and non-strategic firms, and still may distinguish between the two. However, as explained in the preceding paragraph, this test lacks the ability to differentiate between strategic firms and non-strategic firms. Strategic firms are those that deliberately file for bankruptcy with the intention of leveraging bankruptcy courts and creditors to gain strategic advantages, as they have a positive difference between their total liabilities and total assets. On the other hand, non-strategic firms are those that file for bankruptcy due to their poor financial health, without any intention of exploiting bankruptcy filings for personal gain, despite having a positive difference between their total liabilities and total assets. These non-strategic firms may mistakenly appear strategic because they accumulated substantial debt prior to filing for bankruptcy. Thus, if the test results indicate that the financial benefit is endogenous to bankruptcy emergence, this finding can be interpreted as being consistent with both strategic and non-strategic behaviours. On the other hand, if the test results reveal that the financial benefit is exogenous to bankruptcy emergence, it provides support for non-strategic filing behaviour.

Consequently, the 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 estimating multivariate probit models with endogenous regressors. We use financial distress scores (proxied by Altman's (1968) Z-score) at different lags as instrumental variables (to proxy adverse events). Test results show that the coefficient on financial benefit remains significantly *positive* with a dramatic rise in its magnitude. Test results also suggest that companies may start acting strategically from one up to four years before filing for bankruptcy, to maximize their gain from the subsequent bankruptcy filing. Consistent with our tests, we also find that, in 99% of our sample, bankruptcy filings are initiated by managers instead of creditors, which corroborates our results of strategic bankruptcy filings.

Our proposed parsimonious bankruptcy resolution prediction model is anticipated to be valuable for academics, regulators, bankruptcy courts, creditors, and other stakeholders interested in accurately predicting the likelihood of successful bankruptcy resolution for large firms. Notably, one of our significant contributions is the empirical evidence indicating the utilization of strategic bankruptcy filings by large firms as a means to maximize financial benefits. This finding should raise concern and alarm among creditors, bankruptcy courts, and regulators, necessitating their collective intervention to mitigate such strategic practices.

CHAPTER 11 BANKRUPTCY

Corporate bankruptcy in the US is regulated by the 1978 federal Bankruptcy Code. It gives distressed firms or their creditors the possibility to file for bankruptcy, under the protection of a federal bankruptcy court. Bankruptcy filing firms can choose between filing for Chapter 7 (which involves the liquidation of the debtor's property by a court-appointed trustee and making 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).

Firms filing for Chapter 11 bankruptcy protection face two options: to resolve the cause and emerge; or liquidate their assets (Bryan *et al.*, 2002). A Chapter 11 case begins with the filing of a petition, which can be voluntary (filed by the debtor), or involuntary (filed by creditors that meet certain requirements). When filing under this chapter, the debtor remains 'in possession', and retains control over the firm with the powers and duties of a trustee. The debtor may decide to continue to operate its business and, with court approval, even borrow new money (US Court, 2022). Moreover, a Chapter 11 bankruptcy case of a corporation (corporation as the debtor) does not put the personal assets of the stockholders at risk, only the value of their investment in the company's stock. In a partnership bankruptcy case (partnership as the debtor), the partners' personal assets may —in some cases—be used to pay creditors in the bankruptcy case, or the partners themselves may be forced to file for bankruptcy protection (US Court, 2022).

Chapter 11 is considered a debtor-friendly procedure that provides the management with an important leeway, with the aim to limit costlier liquidation (Capkun and Ors, 2021). Chapter 11 of the US Bankruptcy Code is also known as a 'reorganization' bankruptcy, as the debtor's management has 120/180 days to propose a plan for the firm's outstanding contracts reorganization (Jones, 2017; Smith Jr, 1993). The plan could entail the extension of the time for payment of the debtor's obligations, and the reduction of the amounts of those obligations. It can also 'compel creditors to accept stock in full or partial payment of their rights, or even cancel stock or obligations without compensation' (Lehavy, 2002, p. 56). Moreover, it indicates the characteristics of the entity that will emerge as continuing and operating (Lehavy, 2002). Creditors whose rights are affected are entitled to vote on the plan, which may be confirmed by the court upon the attainment of the required votes and compliance with legal requirements (US Court, 2022). Indeed, if—according to the judge—the plan is fair and equitable, then the reorganization plan can be confirmed either with or without the approval of a secured creditor class.[2] Under Chapter 11, debtors can also

[2] The bankruptcy court confirms a reorganization plan if it satisfies three requirements: (1) a two-thirds majority of each class of impaired claimants accepts the plan (unimpaired classes whose contractual rights are not altered by the plan are not allowed to vote on the plan); (2) each dissenting claimant receives at least the amount that it would have received in a Chapter 7 liquidation (the so-called best interest of creditors test); and (3) the plan is feasible, that is, confirmation of the plan is not likely to be followed by a liquidation or a need for further financial restructuring (Lehavy, 2002, p. 56).

negotiate a plan with significant creditor constituencies before filing for bankruptcy; this option is called a 'pre-packaged' bankruptcy plan. Once the judge confirms the plan, it becomes binding on all the involved parties, even those who did not accept it or were impaired under the plan (Lehavy, 2002).

Bankruptcy ends on the disposition date when the judge makes a final ruling in the Chapter 11 bankruptcy case.[3] According to the provisions of the US Bankruptcy Code, four bankruptcy reorganization outcomes are possible: (1) *successful reorganizations* in which firms maintain their corporate identities, continuing as publicly traded firms on national stock exchanges; (2) *partially successful reorganizations* in which firms maintain their corporate identities but fail to meet one or more of the other qualifications stipulated for classification as a successful reorganization; (3) *mergers or acquisitions* where firms publicly report as being acquired by previously existing firms; and (5) *liquidations* where firms are publicly reported as liquidated or without any identifiable successor business.

DATASET, SAMPLE, AND COVARIATES

We build the regression model explaining bankruptcy survival using the UCLA-LoPucki Bankruptcy Research Database (BRD) and the Compustat database to: (1) identify the set of factors explaining firms' emergence likelihood from Chapter 11 bankruptcy filings; (2) evaluate whether strategic emergence is amongst the conditions that best predict companies' emergence prospects by looking at the role of financial benefits; and (3) 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 1 October 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 1950.

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 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)[4] are missing in the BRD database. We also exclude cases in which the filing took place before

[3] Grant (1994) and Franks and Torous (1989) provide a comprehensive overview of the bankruptcy process.

[4] 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.

Table 1

SAMPLE DESCRIPTION

Year (1)	Number of Bankruptcy Filings (2)	Number of Firms Emerged (3)	% of Firms Emerged (4) = (3/2) × 100
1994	10	6	60
1995	11	9	82
1996	13	5	38
1997	11	9	82
1998	20	13	65
1999	27	17	63
2000	56	34	61
2001	61	33	54
2002	38	24	63
2003	35	27	77
2004	20	18	90
2005	13	11	85
2006	10	9	90
2007	7	6	86
2008	23	14	61
2009	60	47	78
2010	14	12	86
2011	15	11	73
2012	11	7	64
2013	15	12	80
2014	11	7	64
2015	21	13	62
2016	33	28	85
2017	17	11	65
2018	13	9	69
2019	9	6	67
Total	574	398	69

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

1994, as an important variable *SALEINT*, which indicates the debtor's 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 recently available information (up to two years) before the bankruptcy filing year if this data is missing.[5]

This allows us to perform the empirical analysis using a relatively long analysis period of 26 years, which includes 574 Chapter 11 filings and 398 successful bankruptcy resolutions of non-financial firms between 1994 and 2019 (see Table 1).[6] Over this time window, we can see that the number of filings

5 The BRD classifies a firm as emerging if the firm is acquired by another firm, provided that the acquiror operates the acquired as a separate business. However, BRD classifies a firm as not emerging if its assets are integrated into a nonbankrupt business of the acquiror or merger partner, provided that the merger partner is bigger in relation to the acquired firm.

6 A complete description of the sampling procedure is detailed in Appendix A.

increased in the year 2001, following the impact of the Dot-com fraud failures in early 2000, and again in 2009, following the global financial crisis[7] (as reported in Table 1, which illustrates the 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 years. Hence, the importance of investigating the set of predictors explaining the probability of emergence from Chapter 11 bankruptcy.

Selection of Covariates

Dependent variable: Bankruptcy emergence In line with the discussion in the previous section, we consider a firm as emerged from Chapter 11 bankruptcy if it either underwent reorganization or has been acquired/merged. It indicates the intent of the debtor to continue the business operations indefinitely after emerging from bankruptcy. More specifically, the dependent variable *EMERGE* is measured as an indicator variable, which equals 1 if firm *i* has been reorganized or acquired/merged, and 0 otherwise.

Independent variables: Predictors of bankruptcy emergence Given the impact of bankruptcy on the economy and society, previous studies have made significant attempts to identify the factors affecting successful bankruptcy reorganization. However, this task has not been easy as a wide range of factors could play a role in predicting firms' emergence from bankruptcy. From juxtaposing literature on the organizational decline, corporate turnarounds, and corporate restructuring, we identified five categories of potential predictors of bankruptcy resolution outcomes, which are outlined in sections below: companies' main features; the judicial and geographical settings in which the litigation takes place; the macroeconomic scenario under which the company operates; and finally, case characteristics, which also captures the governance and strategic decisions made by firms around the bankruptcy process.

In the following section, a comprehensive survey of the factors that could potentially affect firms' emergence from bankruptcy and their possible role in explaining the outcome of successful bankruptcy reorganization is undertaken. Particularly we consider the factors explored in Lopucki and Doherty (2015) to explain the successful bankruptcy resolution of US firms. Appendix B provides an overview of all covariates considered in this study.

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, organizational structure, and industry) as they

[7] In untabulated tests, we consider the influence of these periods in our forecasting model, but we do not find an improvement in its classification performance.

represent the factors typically concentrated on by the empirical literature looking at the determinants of bankruptcy emergence.

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 bankruptcy survival likelihood. In particular, Denis and Rodgers (2007) highlight that larger firms are more likely to reorganize and emerge from Chapter 11, rather than being acquired or liquidated. They attribute this positive impact of the company size on its bankruptcy survival likelihood to the mechanism by which larger companies tend to engage with a wider 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 (e.g., Antill, 2022). The level of leverage reflects the financial health of firms, which in turn, defines their capacity to raise new capital through borrowing and meeting debt obligations. 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. According to George and Hwang (2010, p. 56) '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'. Similar to company size, Denis and Rodgers (2007) report that companies that show higher liability ratios before filing for Chapter 11 are more likely to reorganize themselves than to liquidate or be acquired. To measure the financial fragility of firms, we use the ratio of total liabilities to total assets (*TLTA*) before filing bankruptcy, as reported on the debtor's last annual report before filing bankruptcy. It 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 amortization. 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 year prior to the bankruptcy filing year is positive (*PEBIT*); in other words, we assign *PEBIT* equal to 1 to capture positive *EBIT* ($EBIT > 0$), and 0 otherwise.

Prior research on bankruptcy emergence shows that companies have a higher probability of emerging if they are larger (e.g., Yu and He, 2018). There can be multiple explanations for this result. First, larger companies with a higher probability of emerging can buy assets using funds raised through prior, unsecured bond offerings. Second, they may possess more specialized assets, which accordingly reduces the number of buyers interested in these assets. Third, larger

TABLE 2

INDUSTRY DESCRIPTION

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 the Standard Industrial Classification (SIC) of US firms. SIC Code is a four-digit code that represents a given industrial sector.

firms are more likely to receive government aid due to their national strategic importance. Fourth, larger 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 organizational structure (*EMP*) as a natural logarithm of the number of people 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 have a higher success rate compared to other types of businesses (Lopucki and Doherty, 2015). In their work, they look at five industrial categories: construction, transportation, retail/wholesale, service, and manufacturing/mining. They find companies operating in the 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) relation. To define the list of industrial sectors (*INDUSTRY*), we draw upon the work of Gupta and Chaudhry (2019) categorizing the 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 US firms.

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 voluntary restructurings) for reorganization 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)—including bankruptcy litigation—as well as on emergence. To take into consideration the impact of judicial ability on a company's emergence, we examine three possible predictors. First, *JEXP* is 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 to dispose of the Chapter 11 case. Second, *JEXPD*, a dummy variable, which equals 1 if the judge has completed more than five cases, 0 otherwise.

Similarly, in a few 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 DIP in filing the bankruptcy case) or the attorney has handled before the case being considered.

Case characteristics In the 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, its potential renewal during the bankruptcy process, and an intention to sell the business are crucial for its survival (Lopucki and Doherty, 2015). In particular, the CEO figure is the 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 corporate bankruptcy is also reported to be substantially higher for bankrupt firms. Previous studies also suggest that the removal of 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 becomes more important. Indeed, they can provide firms with a higher likelihood of emergence thanks to their effort and their credibility with financial institutions. However, changes in CEOs' 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. First, *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, 0 otherwise. Second, *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 the values of these assets are closely tied to relationships with these actors. Declining firms divest better than survivors, but at the same time, an 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 organizational 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 may interpret this action as a signal of weakness. Indeed, weaker companies show their intention to sell as they desperately need buyers. Given that decision making is a self-reinforcing process of bankruptcy, project weakness in the eyes of a company's stakeholders could hinder its 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, 0 otherwise.

On the second set of predictors, previous studies report the incidence of the decision undertaken in court. First, the presence of a pre-packaged or pre-negotiated case (i.e., a specialized Chapter 11 filing where companies negotiate a reorganization plan with their 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 reorganization 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.

Second, the length of the bankruptcy process, filing date, and the confirmation date of a Chapter 11 reorganization is also considered. The longer the duration, the lower the likelihood 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 reorganization or the date on which the Chapter 11 case was converted to Chapter 7 or dismissed.

Third, the appointment of a *creditors' committee (CCOM)* by the US Trustee could negatively impact the bankruptcy survival puzzle as the resistance of the committee to debtors' efforts to reorganize could cause company failure (Lopucki and Doherty, 2015). In the 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 US Trustee has appointed a creditors committee to represent the unsecured creditors prior to case disposition, and 0 otherwise.

Fourth, the presence and level of the loan outside the ordinary course of business are considered. A firm during bankruptcy reorganization is known as a 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 (Arora, 2018). 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 that 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 the DIP loan *(DIPTA)* as the ratio of the total DIP loan received to total assets before the bankruptcy filing. This measure of DIP loan obtained per US dollar of total assets is arguably a better measure than *DIPL*.

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 larger 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, without robust analysis, debtor-friendly practices could lead companies to emerge from bankruptcy, 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. First, we consider the city in which the case was filed *(CFILE)*. This variable is categorized as Delaware (DE, 1), New York (NY, 2), and all other cities (OT, 3). Second, 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, and 0 otherwise.

Macroeconomic characteristics Aysun (2014, 2015) explores the link between bankruptcy resolution capacity and economic characteristics and reports the 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. First, we include *PRIME1*, the prime rate of interest one year before the case filing. Second, we include *PRIMEF*, the prime rate of interest on the bankruptcy filing date.

PROBIT MODEL OF BANKRUPTCY EMERGENCE

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 outliers. Descriptive measures of respective covariates for emerged and non-emerged groups of firms reported in Appendix C do not show any extreme variability, suggesting the absence of outliers.[8] However, the correlation matrix in Table 3 shows that some covariates exhibit moderate-to-strong correlations with other covariates, primarily due to their construction. In particular, *JEXP* shows a strong positive correlation of approximately 0.87 with *JEXPD* and *DIPL* with *DIPTA* (0.67). *PRIME1* is strongly positively correlated with *PRIMEF* (0.74), whilst *EMP* exhibits a moderate positive correlation with *CSIZE* (0.47). Amongst the negative correlations, we highlight a moderate correlation in the case of *CFILE* with *JEXP*

[8] For the variable *CEODA*, one observation has negative value. This implies that the CEO resigned before filing for bankruptcy. We replace this negative value with 0. Additionally, about 10% of the observations in the top decile shows values of *CEODA* as high as 800 years. This appears to be due to unavailable (coded as 09sep9999) and missing dates of CEOs last working date (DateCeoEnd) in the BRD database. Thus, to maximize the sample size, we replace all such observations with the mean of available observations (1.37 years).

TABLE 3

CORRELATION MATRIX

Variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
CSIZE	(1)	1.00																					
TLTA	(2)	–0.04	1.00																				
PEBIT	(3)	0.11	0.01	1.00																			
EMP	(4)	0.47	–0.01	0.26	1.00																		
INDUSTRY-M	(5)	0.02	0.07	0.12	0.06	1.00																	
INDUSTRY-R	(6)	–0.08	–0.10	–0.04	0.34	–0.39	1.00																
JEXP	(7)	0.06	0.09	–0.04	–0.01	–0.01	–0.06	1.00															
JEXPD	(8)	0.07	0.06	–0.02	0.00	–0.01	–0.05	0.87	1.00														
AEXP	(9)	0.30	0.10	–0.02	0.07	–0.04	0.00	0.28	0.28	1.00													
CEOR	(10)	0.05	0.10	0.18	0.17	0.17	–0.06	–0.01	0.02	–0.04	1.00												
CEODA	(11)	0.11	0.04	0.05	0.09	0.11	–0.06	0.01	0.00	0.07	0.01	1.00											
SALEINT	(12)	–0.18	–0.18	–0.14	–0.15	0.00	0.01	0.10	0.08	–0.03	–0.24	–0.23	1.00										
PREAGR	(13)	–0.05	0.24	0.06	–0.09	–0.05	–0.10	0.13	0.10	0.16	0.06	0.07	–0.26	1.00									
DURATION	(14)	0.20	–0.14	0.03	0.21	0.10	0.12	–0.05	–0.04	0.02	0.05	0.06	0.00	–0.42	1.00								
CCOM	(15)	0.12	–0.15	0.00	0.13	0.09	0.06	–0.06	–0.03	–0.04	–0.04	–0.08	0.18	–0.51	0.33	1.00							
CFILE	(16)	–0.04	–0.04	0.00	–0.11	–0.06	–0.03	–0.55	–0.49	–0.15	–0.10	–0.13	–0.03	–0.12	0.01	0.15	1.00						
HCCTODE	(17)	–0.03	–0.09	–0.11	–0.17	–0.15	–0.06	0.05	0.06	–0.06	–0.18	–0.11	0.07	–0.05	–0.08	0.07	0.15	1.00					
BSHOP	(18)	0.11	0.06	0.00	0.09	–0.02	–0.01	0.47	0.40	0.19	0.03	0.07	0.06	0.12	–0.07	–0.03	–0.63	0.01	1.00				
DIPL	(19)	0.02	0.02	0.00	–0.02	0.07	–0.02	0.24	0.22	0.27	0.05	–0.05	0.04	0.04	–0.17	0.02	–0.06	–0.02	0.12	1.00			
DIPTA	(20)	–0.04	0.12	0.06	0.04	0.05	0.06	0.19	0.16	0.22	0.05	–0.01	0.01	–0.02	–0.08	0.04	–0.09	–0.06	0.14	0.67	1.00		
PRIMEI	(21)	0.01	–0.11	0.11	0.20	0.04	0.10	–0.30	–0.28	–0.36	0.03	0.13	–0.06	–0.21	0.29	0.13	0.01	–0.05	–0.13	–0.51	–0.32	1.00	
PRIMEF	(22)	–0.11	–0.08	0.08	0.15	–0.06	0.19	–0.31	–0.26	–0.37	0.05	0.08	–0.08	–0.15	0.26	0.08	0.02	–0.08	–0.11	–0.46	–0.24	0.74	1.00

Notes: This table reports correlation among the set of covariates estimated over the sample period 1994–2019.

(–0.55) and *JEXPD* (–0.49), supporting the argument that the bankruptcy courts located in other cities, except DE and NY, are associated with judges with less experience (in terms of the number of cases completed at confirmation of the case being considered). Similarly, *BSHOP* and *CFILE* (–0.63) 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 *(PREAGR)* are negatively associated with the appointment of a creditors committee *(CCOM)* to represent the unsecured creditors prior to case disposition (–0.51). Finally, a moderate correlation is observed between *PRIME1* and *DIPL* (–0.51) 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 below.

Univariate Probit Regression and Average Marginal Effects

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[9] (AME). The results of univariate regression estimates are presented in Table 4.

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 positive EBIT before filling (*PEBIT*). A positive bivariate relation is also found between *EMERGE* and *EMP*. Indeed, an increase in the number of employees is associated with an increase in a firm's emergence likelihood. Surprisingly, we also find that firms with higher leverage levels are more likely to emerge, as we find a positive coefficient on the ratio of total liabilities to total assets, *TLTA*, which defies the conventional wisdom. Regarding the variable INDUSTRY, we test the statistical significance of respective industrial classification from 1 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. Thus, we include a dummy variable corresponding to retail industrial classification (*INDUSTRY-R*) and a dummy variable for manufacturing firms (*INDUSTRY-M*). We also include *CFILE* as a dummy variable equalling 1 for 'OT' category (all other cities apart from Delaware and New York), and 0 otherwise, because it yields the highest significance among DE and NY.

9 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 this 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, p. 451) for detailed discussion on this topic.

TABLE 4

UNIVARIATE REGRESSION ANALYSIS

Variable (1)	Sign (2)	Coefficient (3)	Standard Error (4)	AME in % (5)	Rank of AME (6)
DIPTA	+	1.538***	0.456	52.97	1
CEOR	+	1.634***	0.125	41.11	2
CCOM	–	–1.068***	0.190	–35.34	3
SALEINT	–	–1.109***	0.125	–34.17	4
PREAGR	+	1.062***	0.134	33.34	5
TLTA	+	1.008***	0.174	33.12	6
INDUSTRY-R	–	–0.508***	0.142	–17.45	7
CEODA	+	0.464***	0.072	14.72	8
DIPL	+	0.427***	0.116	14.67	9
JEXPD	+	0.412***	0.113	14.15	10
CFILE	–	–0.382***	0.112	–13.15	11
PEBIT	+	0.382***	0.110	13.13	12
BSHOP	+	0.366***	0.121	12.66	13
INDUSTRY-M	+	0.256**	0.111	8.89	14
CSIZE	+	0.171***	0.060	5.93	15
DURATION	–	–0.164***	0.040	–5.59	16
AEXP	+	0.160***	0.041	5.47	17
JEXP	+	0.149***	0.046	5.12	18
PRIME1	–	–0.093***	0.025	–3.17	19
HCCTODE	–	–0.088*	0.049	–3.07	20
EMP	+	0.074**	0.035	2.58	21
PRIMEF	–	–0.068***	0.024	–2.36	22

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ (two-sided test). This table reports univariate probit regression estimates of respective covariates using *EMERGE* as the dependent variable. 'Sign' (column 2) represents the 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.

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

Mixed results are present for case characteristics. *CEOR*, *CEODA*, *PREAGR*, *DIPL*, and *DIPTA* show positive explanatory power; conversely, *SALEINT*, *DURATION*, and *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 *(PREAGR)*, 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, we find *SALEINT* to be the strongest single predictor of failure during bankruptcy. In contrast, the univariate regression results show discordant findings in the case of a US Trustee appointed creditors committee to represent the unsecured creditors prior to case disposition *(CCOM)*. This negative relation shows that companies are more likely to agree to a liquidation plan if a creditors committee is appointed.

Considering 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 the court is further supported by the negative bivariate relation between a company's emergence with both *HCCTODE* and *CFILE* in all other cities except New York and Wilmington, Delaware. Indeed, the further 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.

Baseline Multivariate Probit Model

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

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

This specification allows us to investigate companies' emergence ($EMERGE_{it}$) likelihood as a function of a set of the 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 the variables based on the magnitude of their AMEs.[10] 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 the 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). Among the prespecified criteria, we exclude a covariate from the multivariate model if, when introduced: (1) it affects the sign of any previously added covariate; (2) it bears the opposite sign to that in the univariate regression; (3) it bears the expected sign but has a p-value greater than 0.05; and (4) it makes a

[10] 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).

previously added covariate insignificant with a p-value greater than 0.05. While developing multivariate models, this method of covariate introduction reasonably addresses the multicollinearity problem and provides a parsimonious set of covariates explaining the variance of the outcome variable. As stated in equation 2, this gives us a parsimonious baseline multivariate probit model with ten covariates, all of which are highly significant (see Table 5) in explaining bankruptcy resolution likelihood.[11]

$$\begin{aligned} EMERGE_{\mathrm{i,t}} = \alpha &+ \beta_1 DIPTA_{i,t} + \beta_2 CEOR_{i,t} + \beta_3 CCOM_{i,t} + \beta_4 SALEINT_{i,t} \\ &+ \beta_5 PREAGR_{i,t} + \beta_6 TLTA_{i,t} + \beta_7 CEODA_{i,t} + \beta_8 INDUSTRY - R_{i,t} \\ &+ \beta_9 JEXPD_{i,t} + \beta_{10} PRIMEF_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{2}$$

Within the firm characteristics, operating in retail sectors (*INDUSTRY-R*) has a negative and statistically significant impact on companies' emergence. The replacement of the CEO after filing for Chapter 11 *(CEOR)* carries a positive coefficient with a statistically significant result at the 0.01 level. This supports the importance of releasing the company from potential 'threat-rigidity' by injecting fresh management resources to initiate strategic change. If the CEO is not replaced, the time between the CEO leaving the post and the bankruptcy filing date *(CEODA)* also bears a positive relation to emergence, which signals confidence in the existing leadership (implying that the CEO was not held responsible for bankruptcy filing), and that retaining highly skilled CEOs with firm-specific knowledge improves firm performance (Evans III *et al.*, 2013). Contrary to our expectation, a rise in total liabilities to total assets *(TLTA)* has a positive and statistically significant impact on the emergence likelihood. We further test this relation. 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 initialization tends to reduce the costs and duration of the reorganization 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 bankrupt companies with wider flexibility to manage their retrenchment and undertake strategic action via the use of the DIP financing tool. In accordance with Lopucki and Doherty (2015), announcing the intention to sell a company's business *(SALEINT)* dramatically increases the risk of unsuccessful resolution. Further, the appointment of a creditors committee to unsecured creditors *(CCOM)* significantly reduces the likelihood of resolution, signalling that these creditors may prefer liquidation. We find that a judicial characteristic such as

[11] We also implemented commonly used variable selection techniques, stepwise regressions, and LASSO, as alternative model-building strategies (See Appendix D). However, the baseline model obtained using the model building strategy suggested by Gupta *et al.* (2018) gives the best parsimonious model with almost identical values of adjusted R^2 and classification performance. LASSO suggests a model with 18 covariates, of which 11 are insignificant, whereas, stepwise suggests a model with 11 covariates and a negative coefficient on *lnHCCTODE* (its positive in the univariate regression).

TABLE 5

BASELINE MULTIVARIATE PROBIT MODEL

Variable (1)	Coefficient (2)	Standard Error (3)	AME in % (4)
DIPTA	2.359*** (2.950)	0.799	31.93
CEOR	2.487*** (11.389)	0.218	33.67
CCOM	–0.773** (–2.254)	0.343	–10.47
SALEINT	–0.663*** (–3.304)	0.201	–8.97
PREAGR	1.091*** (4.504)	0.242	14.77
TLTA	0.465** (2.111)	0.220	6.30
CEODA	0.794*** (5.914)	0.134	10.74
INDUSTRY-R	–0.448** (–1.973)	0.227	–6.06
JEXPD	0.478*** (2.595)	0.184	6.47
PRIMEF	–0.088** (–2.012)	0.043	–1.18
Constant	–1.253** (–2.381)		
Log likelihood	–140.82		
LR Chi2	425.94		
Pseudo R^2	0.6020		
AUROC-W	0.9549		
AUROC-H	0.9145		
N = 1	398		
N = 0 + 1	574		

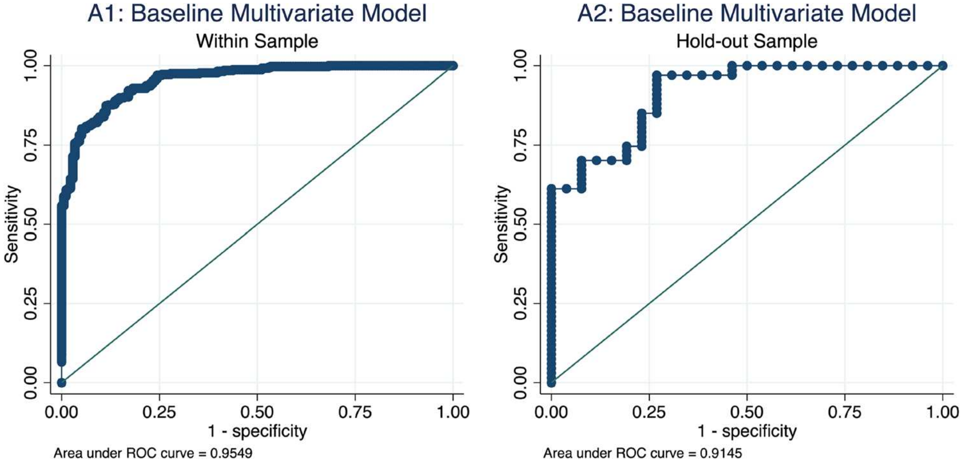
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ (two-sided test). z-statistics in parentheses. Column 2 reports regression coefficients (β) of the multivariate probit model. Column 3 reports standard errors of respective coefficients, and column 4 reports their average marginal effects in percentage. Models' goodness of fit and classification performance measures are reported in the last seven rows. AUROC-W is the within sample area under the receiver operating characteristic, and AUROC-H is for the hold-out sample. 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 2019.

the experience of the judge *(JEXPD)* is positively related to emergence. Lastly, we find that the prime interest rate on the bankruptcy filing date *(PRIMEF)* is negatively related to emergence.

Furthermore, as indicated by Gupta *et al.* (2018), we evaluate the classification performance of the multivariate model using a non-parametric classification measure, namely the area under receiver operating characteristic curve (AUROC). As reported in Figure 1, AUROC for this model is about 95%, suggesting excellent within-sample classification performance of the multivariate model. To assess the out-of-sample

FIGURE 1

RECEIVER OPERATING CHARACTERISTIC CURVE



classification performance, we follow the steps suggested by Gupta *et al.* (2018). First, we estimate the multivariate prediction model using observations until the year 2014 and, using these estimates, we predict the probabilities for the year 2015. We then include 2015 in the estimation sample and predict probabilities for 2016 and so on, until the year 2019. We then use these predicted probabilities from the years 2015 to 2019 to estimate the out-of-sample AUROC, which is about 91%, thus suggesting excellent out-of-sample classification performance of our proposed model. However, the shape of the ROC curve is not concave due to the very low number of outcome events in the hold-out sample. This might result in misleading estimates of AUROC. Thus, we suggest interpreting our out-of-sample AUROC result carefully.

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, p. 125) since the implementation of the Bankruptcy Reform Act of 1978 (e.g., Flynn and Farid, 1991). Likewise, according to 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 a 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 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 get closer to the end of their tenure (Zwiebel, 1996).

Additionally, distressed firms are usually characterized by abnormally large leverage ratios and small equity proportions in their capital structure (Altman *et al.*, 2019). Corporate investment risk-taking often changes when a firm with high leverage approaches distress or bankruptcy. In their seminal study, Jensen and Meckling (1976) hypothesize that managers acting in shareholders' best interest have incentives to substitute safer with riskier assets, with the incentives being higher in firms facing distress or bankruptcy risk. This hypothesized increased risk-taking in a firm's investments, referred to as risk-shifting or asset substitution, often results in a higher overall cost to the firm (Jensen and Meckling, 1976). A small number of studies, including Aretz *et al.* (2019), Favara *et al.* (2017), Gilje (2016), and Becker and Strömberg (2012), indeed confirm that high distress risk often encourages the executives of industrial firms to engage in higher risk-taking.

This is because, in high-leverage or high-risk states, equity holders benefit from successful outcomes of high-risk projects, while losses from unsuccessful projects are borne by lenders. This asymmetry between who receives the gains and losses from a project encourage equity holders to maximize the amount of risk a firm undertakes when leverage is high. In our setting, this implies that firms facing bankruptcy risk could make strategic decisions to undertake risky projects or maximize their leverage levels as they have less to lose if the investments fail. Consistent with this risk-shifting hypothesis, Li *et al.* (2017) find that distressed firms tend to overinvest, destroy value, and exhaust their cash flows.

From an organizational perspective, companies could also proactively file for Chapter 11 bankruptcy 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 companies' structure with their strategic competencies, annihilating competition (Borenstein and Rose, 2003) or even negotiating better terms with stakeholders (Delaney, 1999). This, in turn, provides them with a higher likelihood of emerging from bankruptcy (Flynn and Farid, 1991, p. 73). For instance, companies in financial distress that culminate in 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 US 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 reorganize in bankruptcy (and subsequently emerge as a going concern), both when they have unfavourable relationships and/or contractual 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 reorganization 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 DIP provision (DIP financing). Whilst the costs are the same for all types of companies, the benefits are significantly higher for firms with a lower market-to-book value (i.e., low-value) than firms with a higher market-to-book value (i.e., high-value) (Li, 2013). 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 for Chapter 11, low-value firms reveal adverse information (namely, true firm value) to shareholders through a 'signalling' effect.

In light of the above discussion, 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 the 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.

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. Leverage analysis of our sample confirms this assertion (see Table 6). Column 2 of Table 6 shows that the leverage ratio (*TLTA*, total liabilities/total assets) of all firms increases from about 0.74 to about 1.06 within five years preceding the bankruptcy filing year. However, the leverage analysis of emerging and non-emerging groups of firms reveals interesting facts. Unlike their non-emerging counterparts, the emerging group shows a persistent increasing trend of leverage levels up to four years preceding the bankruptcy filing year (as the difference of the means between two

TABLE 6

LEVERAGE ANALYSIS OF BANKRUPTCY FILING FIRMS

Year	Mean Leverage – Full Sample	*t-test* – Column (2) (t–(t–1))	Mean Leverage – Non-eEmerging Firms	*t-test* – Column (4) (t– (t–1))	Mean Leverage – Emerging Firms	*t-test* – Column (6) (t–(t–1))	*t-test* (6) – (4)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t	1.062	0.107***	0.925	0.161***	1.124	0.081***	0.199***
t–1	0.955	0.102***	0.764	0.027	1.043	0.138***	0.279***
t–2	0.853	0.045***	0.737	0.057***	0.905	0.042	0.168***
t–3	0.808	0.058	0.680	−0.014	0.863	0.090*	0.183***
t–4	0.750	0.006	0.694	0.002	0.773	0.008	0.079**
t–5	0.744		0.692		0.765		0.073*

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ (one-tailed test). Leverage is calculated as the ratio between total liabilities and total assets. *t-test* represents two group mean comparison test.

successive years, $TLTA_t - TLTA_{(t\text{–}1)}$, in column 7 remain positive), with the ratio surpassing 1 in years *t* and *t*–1, suggesting total debt is higher than total assets. This is surprising as the non-emerging group with significantly lower leverage levels (column 4) is less likely to survive bankruptcy, while the emerging group with significantly higher leverage levels (column 6) is more likely to emerge successfully. Additionally, in any given year (*t, t*–1*, t*–2*,* ……or *t*–5), the leverage ratio of the emerging group is significantly higher than its non-emerging counterpart (see column 8). Taken together, this evidence suggests that some firms may act strategically to build up their leverage levels in the years preceding the bankruptcy filing year to maximize their financial benefits in the event of bankruptcy reorganization. We test this assertion more rigorously in our subsequent analysis.

Intuitively, it appears that the higher the amount of debt, the lower the likelihood of a successful bankruptcy resolution. If we compute a firm's financial benefit from bankruptcy filing as follows:

$$Financial\ Benefit_{it} = \text{maximum}\left[(TL_{it} - TA_{it}), 0\right] \tag{3}$$

where *Financial Benefit*$_{it}$ is the financial benefit from bankruptcy filing for a company *i* in the period *t*, TL_{it} is its total liabilities in period *t* and TA_{it} is its total assets in the period *t*. Then, we would expect a *negative* relationship between financial benefits and firms' likelihood of emerging from Chapter 11 bankruptcy. Otherwise, a *positive* relation between emerging from bankruptcy and financial benefit from filing, *ceteris paribus*, is taken as evidence of *strategic behaviour*. Although this relation between financial benefit and the 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), Fay *et al.* (2002) and Zhang *et al.* (2015) successfully use a similar specification to report strategic behaviour in household bankruptcy filings in the US. Besides, subsequent statistical tests using this specification give results in favour of the hypothesis.

We test the presence of strategic behaviour in bankruptcy emergence by supplementing the bankruptcy emergence model with an additional covariate, *FB*, to the model specification in equation 2. In the analysis of financial benefit from filing, we take one-year lag of the natural logarithm of *Financial Benefit*$_{it}$; that is, 1n(*Financial Benefit*$_{i,t-1}$ + 1) (*FB*$_{it}$). In line with Fay *et al.* (2002), we believe *FB* must be positive. We introduce the strategic behaviour in the probit regression specification of bankruptcy emergence as follows:

$$\begin{aligned}\boldsymbol{EMERGE}_{\mathbf{i,t}} = \alpha + \boldsymbol{\beta_1 FB_{i,t}} + \beta_2 DIPTA_{i,t} + \beta_3 CEOR_{i,t} + \beta_4 CCOM_{i,t} + \beta_5 SALEINT_{i,t} \\ + \beta_6 PREAGR_{i,t} + \beta_7 TLTA_{i,t} + \beta_8 CEODA_{i,t} + \beta_9 INDUSTRY-R_{i,t} \\ + \beta_{10} JEXPD_{i,t} + \beta_{11} PRIMEF_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{4}$$

We report the results in Table 7. Surprisingly, we find a positive coefficient of financial benefit, indicating that the likelihood of emerging from Chapter 11 bankruptcy increases with increasing financial benefits. This result is similar to Fay *et al.* (2002) and Zhang *et al.* (2015), who report a positive relationship between financial benefits and household bankruptcy filing decisions. It also resonates with the finding of Adler *et al.* (2013), who show that, in anticipation of bankruptcy, firms tend to increase their level of leverage.

Thus, the possibility of any strategic behaviour in bankruptcy resolution cannot be ignored. Additionally, since *FB* is significant at the 5% level and its inclusion renders *TLTA* insignificant due to the strong correlation between them (about 0.7), we re-estimate the model excluding *TLTA*. We do so as the primary objective of this analysis is to explore the role of financial benefits in explaining firms' likelihood of emerging from Chapter 11 bankruptcy. Further, we also take out *PREAGR* from the estimation because it represents a two-way agreement between managers and creditors, overriding the principal ethos of a strategic bankruptcy filing. Its exclusion ensures that our estimate of *FB* is not confounded by parameters threatening its credibility. The results are presented in columns 4 and 5 of Table 7. The exclusion of *TLTA* and *PREAGR* increases the significance of *FB* to the 1% level, with a marginal increase in the magnitude of its coefficient and a marginal reduction in its standard error. Thus, subsequent analyses are based on the model reported in column 4 of Table 7.

It might be argued that our results are driven by sample dependency. Therefore, to mitigate this concern and to allow the generalizability of our results, we use a technique known as the entropy balancing method. This technique is theoretically and empirically superior to propensity score matching (Hainmueller, 2012, 2013)

Table 7

MULTIVARIATE PROBIT MODELS FOR STRATEGIC BEHAVIOUR IN BANKRUPTCY RESOLUTION

Variable (1)	*EMERGE* with *TLTA* and *PREAGR* (2)	Std. Error (3)	*EMERGE* without *TLTA* and *PREAGR* (4)	Std. Error (5)
FB	**0.134****	**0.059**	**0.137*****	**0.044**
	(2.238)		**(3.119)**	
DIPTA	2.408**	1.008	1.831**	0.921
	(2.387)		(1.988)	
CEOR	2.541***	0.235	2.378***	0.214
	(10.789)		(11.101)	
CCOM	–0.759**	0.368	–1.229***	0.325
	(–2.062)		(–3.777)	
SALEINT	–0.560**	0.223	–0.709***	0.212
	(–2.502)		(–3.347)	
PREAGR	1.099***	0.262	–	–
	(4.185)		–	
TLTA	–0.125	0.357	–	–
	(–0.349)		–	
CEODA	0.773***	0.143	0.714***	0.133
	(5.412)		(5.352)	
INDUSTRY-R	–0.511**	0.250	–0.517**	0.236
	(–2.041)		(–2.191)	
JEXPD	0.485**	0.204	0.566***	0.195
	(2.378)		(2.904)	
PRIMEF	–0.072	0.049	–0.102**	0.046
	(–1.448)		(–2.176)	
Constant	–0.943*	0.572	–0.003	0.422
	(–1.647)		(–0.007)	
Log likelihood	–116.00		–125.95	
LR Chi2	375.75		355.85	
Pseudo R^2	0.6182		0.5855	
N = 1	333		333	
N = 0 + 1	487		487	

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ (two-sided test). z-statistics in parentheses. Columns 2 and 4 report regression coefficients (β) of multivariate probit models with and without *TLTA* and *PREAGR*, respectively. Columns 3 and 5 report the standard errors of respective coefficients. Models' goodness of fit and classification performance 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 2019.

and is increasingly used in recent literature (e.g., Shroff *et al.*, 2017; Pierk, 2021). In this method, the control (independent) variables, apart from *FB* (treatment variable), are balanced in their three moments (mean, variance, and skewness) between firms where financial benefit exists against those where it does not. This method mitigates sample dependency and allows us to gauge the true effect of financial benefit on the likelihood of a firm emerging from bankruptcy. Therefore, we create a new dummy variable (*FBD*), which equals 1 if the financial benefit exists, otherwise 0. Our main results remain qualitatively unchanged. We present the entropy balanced regression estimates in Table 8.

Table 8, Panel A, shows that the mean of *EMERGE* for firms with financial benefits is 0.87, which is greater than for firms without financial benefits (0.59). In fact, this suggests that firms with financial benefits emerge more compared to their counterparts. Panel A also shows that all three moments (mean, variance, and skewness) of control variables after entropy balancing are reasonably matched between firms with and without financial benefits. Table 8, Panel B, shows the regression results. Column 2 reports the coefficient of *FBD* (0.744), which is positive and significant at 1%, suggesting that firms with financial benefits are more likely to emerge. Our results remain qualitatively the same, even after the inclusion of *TLTA* and *PREAGR*. Together, these results suggest that firms may act strategically in a bankruptcy filing decision to pursue financial gains.

Adverse Event, Financial Benefit, and Bankruptcy Resolution

However, the simple empirical relation between bankruptcy emergence and *FB* presented in equation (4) does not consider more realistic relations among financial benefit, adverse events, and strategic behaviour (Zhang *et al*., 2015). For example, financial benefits 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, the 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, as it uses debt to pay for expenses, consistent with non-strategic behaviour. Moreover, a non-strategic firm may appear strategic to analysts if it rolls over debt as long as there is the hope of repaying it. This leads to higher measured financial benefits before filing, despite no intention to abuse bankruptcy law. In other words, the financial benefit is affected by both strategic and non-strategic behaviour, and a positive coefficient on financial benefit alone is insufficient to distinguish between the two behaviours.

The subsequent test (employing the empirical design suggested by Zhang *et al.* (2015) in the context of household bankruptcy) partially disentangles the role of financial benefit, adverse events, and strategic behaviour: it allows for a positive relation between bankruptcy emergence and financial benefit for both strategic and non-strategic firms, and still may distinguish between the two. However, this test cannot distinguish between strategic firms and non-strategic firms that 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 the 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 a two-step decision-making process. In the first step, the firm receives noisy adverse 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 a Chapter 11 filing and

TABLE 8

ENTROPY BALANCED REGRESSION ANALYSIS

Panel A: Descriptive statistics

	Financial Benefit (*FBD* = 1) (N = 156)			No Financial Benefit (*FBD* = 0) (N = 330)		
Dependent Variable	Mean	Variance	Skewness	Mean	Variance	Skewness
EMERGE	0.871	0.112	–2.224	0.596	0.241	–0.365
Matching Control Variables Before Entropy Balancing						
DIPTA	0.099	0.030	2.346	0.060	0.014	2.586
CEOR	0.699	0.212	–0.866	0.571	0.246	–0.287
CCOM	0.750	0.189	–1.155	0.861	0.120	–2.087
SALEINT	0.135	0.117	2.141	0.320	0.218	0.771
CEODA	1.545	2.581	2.917	1.271	3.018	3.210
INDUSTRY-R	0.128	0.113	2.224	0.196	0.158	1.529
JEXPD	0.474	0.251	0.103	0.396	0.240	0.426
PRIMEF	5.404	4.891	0.619	5.734	5.101	0.343
Matching Control Variables After Entropy Balancing						
DIPTA	0.099	0.030	2.346	0.099	0.030	2.348
CEOR	0.699	0.212	–0.866	0.698	0.212	–0.861
CCOM	0.750	0.189	–1.155	0.749	0.189	–1.149
SALEINT	0.135	0.117	2.141	0.135	0.117	2.132
CEODA	1.545	2.581	2.917	1.544	2.580	2.920
INDUSTRY-R	0.128	0.113	2.224	0.129	0.113	2.217
JEXPD	0.474	0.251	0.103	0.475	0.250	0.102
PRIMEF	5.404	4.891	0.619	5.400	4.887	0.625

Panel B: Entropy balanced probit regression

Variable (1)	Coefficient (2)	Z-Statistics (3)	Std. Error (4)
FBD	**0.744*****	3.326	0.743
DIPTA	2.161***	2.652	2.160
CEOR	2.668***	9.738	2.667
CCOM	–1.511***	–5.364	–1.511
SALEINT	–1.165***	–3.941	–1.164
CEODA	0.805***	4.584	0.805
INDUSTRY-R	–0.616**	–2.337	–0.615
JEXPD	0.759***	3.216	0.759
PRIMEF	–0.119**	–2.427	–0.119
Constant	0.176	0.418	0.176
Log pseudolikelihood	–53.44		
Wald Chi2	185.73		
Pseudo R^2	0.6295		
N = 1	156		
N = 0 + 1	487		

Notes: Panel A of this table report descriptive measures of control variables used in entropy balancing, before and after entropy balancing. *FBD* is a dummy variable equaling 1 if the financial benefit is positive, and 0 otherwise. Panel B reports entropy balanced probit regression results. Coefficients are presented in column 2 (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ indicate the statistical significance of two-tailed test), robust z-statistics are presented in column 3, and standard errors are in column 4. This table reports our regression results using entropy balancing. Our results remain qualitatively unchanged even after the inclusion of *TLTA* and *PREAGR*.

updates its debt level to maximize its gain from any subsequent bankruptcy filing. Thus, a strategic firm is one that, 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 maximize 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 considering the pre-evaluated likelihood of emerging from bankruptcy (after realizing 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 proceeding, we need to define a variable that effectively captures adverse events or the deteriorating financial health of a firm. We proxy this with the popular Z-Score proposed by Altman (1968) estimated as follows:[12]

$$Z-Score_{it} = 1.2\frac{WC_{it}}{TA_{it}} + 1.4\frac{RE_{it}}{TA_{it}} + 3.3\frac{EBIT_{it}}{TA_{it}} + 0.6\frac{E_{it}}{D_{it}} + 0.999\frac{S_{it}}{TA_{it}} \tag{5}$$

Where *WCit* is the working capital of firm *i* in the year *t*, *REit* is retained earnings, *EBITit* is earnings before interest and taxes, *Eit* is the market value of equity, *Dit* is total liabilities, *Sit* is sales, and *TAit* is total assets. This appears perfectly reasonable as higher values of working capital, retained earnings, earnings, market value, and sales signal growth and profitability. Thus, the higher the value of the Z-Score, the better the financial health of a firm and vice-versa. This means that there exists a *negative* relation between firms' likelihood of entering financial distress or bankruptcy and Z-Score. Similarly, among the firms that filed for Chapter 11 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* relation between Z-Score and firms' likelihood of emerging from bankruptcy. However, the univariate regression estimates reported in Table 9 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 consistent and counterintuitive. This may be possible if firms strategically update their leverage

[12] Although Z-Score is almost five decades old, it is still widely used as a proxy of firms' financial health or distress status (see among others Monsen, 2022; Li *et al*., 2021; Edwards *et al*., 2016). Also see Altman *et al*. (2017) for an updated and additional discussion on the relevance of the Z-Score in recent times.

TABLE 9

UNIVARIATE PROBIT ESTIMATES FOR Z-SCORE

Variable	Coefficient	Standard Error
Z-Score (T-1)	–0.1811***	0.0366
Z-Score (T-2)	–0.0922***	0.0273
Z-Score (T-3)	–0.0924***	0.0265
Z-Score (T-4)	–0.0429***	0.0203
Z-Score (T-5)	–0.0767***	0.0266

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ indicate significance of a two-tailed test.

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.

Coming back to the test of the 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 10. Columns 2 to 6 report multivariate regression models for different lags (in years) of Z-Score (lag 1 to 5). Except for Model 1, the test results suggest the presence of strategic behaviour in bankruptcy resolution up to five years prior to the bankruptcy filing year. In particular, the coefficients of financial benefit are positive and significant at 0.01 level for Models 2 and 4, and at 0.05 levels for Models 3 and 5, while the coefficients of Z-Score are insignificant, except in model 1.

However, this simple empirical relation between bankruptcy resolution and financial benefit conflates more realistic relations between financial benefit, adverse events, and strategic behaviour. To disentangle some of these relations, 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 they emerge if they file for bankruptcy.

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,

TABLE 10

MULTIVARIATE PROBIT MODELS FOR STRATEGIC BEHAVIOUR IN BANKRUPTCY RESOLUTION WITH ADVERSE EVENT (Z-SCORE)

Variable (1)	Model 1 (2)	Model 2 (3)	Model 3 (4)	Model 4 (5)	Model 5 (6)
FB	**0.087**	**0.160*****	**0.137****	**0.152*****	**0.131****
	(1.433)	(2.671)	(2.372)	(2.587)	(2.164)
Z-score (lag 1)	**–0.143****				
	(–2.283)				
Z-score (lag 2)		**0.017**			
		(0.450)			
Z-score (lag 3)			**–0.008**		
			(–0.241)		
Z-score (lag 4)				**0.020**	
				(0.631)	
Z-score (lag 5)					**–0.002**
					(–0.054)
DIPTA	2.483**	2.228*	2.148*	2.354*	2.293*
	(2.276)	(1.873)	(1.840)	(1.921)	(1.842)
CEOR	2.444***	2.587***	2.426***	2.458***	2.398***
	(10.070)	(9.583)	(9.273)	(8.845)	(8.287)
CCOM	–1.193***	–1.297***	–1.223***	–1.302***	–1.384***
	(–3.226)	(–3.495)	(–3.096)	(–3.107)	(–3.138)
SALEINT	–0.884***	–1.016***	–1.063***	–1.119***	–1.098***
	(–3.557)	(–3.844)	(–3.984)	(–4.061)	(–3.864)
CEODA	0.575***	0.639***	0.593***	0.581***	0.585***
	(4.078)	(4.276)	(4.078)	(3.969)	(3.771)
INDUSTRY-R	–0.458	–0.722**	–0.723**	–0.995***	–1.085***
	(–1.595)	(–2.453)	(–2.465)	(–3.195)	(–3.198)
JEXPD	0.594**	0.616***	0.590**	0.636**	0.515**
	(2.574)	(2.596)	(2.456)	(2.567)	(1.985)
PRIMEF	–0.037	–0.074	–0.055	–0.060	–0.049
	(–0.679)	(–1.315)	(–0.982)	(–1.024)	(–0.795)
Constant	–0.138	–0.188	–0.112	–0.102	0.114
	(–0.288)	(–0.386)	(–0.218)	(–0.198)	(0.199)
Log likelihood	–93.49	–85.71	–85.37	–79.19	–70.68
LR Chi2	302.66	287.26	265.78	249.83	227.74
Pseudo R^2	0.6181	0.6263	0.6089	0.6120	0.6170
N = 1	257	249	238	225	207
N = 0 + 1	385	366	349	328	299

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ (two-sided test). z-statistics 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 2019.

determines both their inability to meet their financial obligations toward creditors and their ability to emerge from bankruptcy. Companies behaving strategically determine their debts to maximize the financial benefit they can obtain from 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 impact a firm's bankruptcy resolution likelihood. It serves as an instrumental variable that directly affects financial benefit, *FB*. As adverse events are exogenous to companies' likelihood of emerging from Chapter 11, it operates more as a shock to firms.

The rationale behind the choice of Z-score as an instrumental variable might not appear convincing. It springs from the fact that any random adverse event to a firm will subsequently affect (adversely) one or more factors of the Z-score (i.e., working capital, retained earnings, earnings, market value or sales), which in turn will affect the Z-score. Thus, Z-score can be considered an aggregate measure that captures the effects of multiple adverse random events faced by a firm. Although this might not represent a perfect instrument for *FB*, subsequent test results do not disapprove of this choice either.

Indeed, a decrease in Z-score leads companies to lose credibility, which in turn leads to reduced access to finance and external credit. Hence, this generates exogenous 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 11. For each model, we perform a Wald 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 hypothesis 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 11 reports multivariate probit models with endogenous regressors.

The coefficient of *FB* for respective models is significant in IV Models 1, 2, and 3, and shows a dramatic increase in magnitudes compared to models reported in Table 10, indicating the pivotal role of *FB* in companies' emergence. The coefficient of *FB* is maximum (0.58) when only Z-score with a one-year lag is used (IVModel 1) and shows a 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 in Models 4 and 5, which does not corroborate with the endogeneity of financial benefit, whereas Models 1, 2, and 3 show values of Ω that are statistically significant from zero, which are consistent with financial benefits being endogenous. We interpret the 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 the 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 when more than one instrument is used. In the models, we fail to reject the

TABLE 11

MULTIVARIATE PROBIT MODELS FOR STRATEGIC BEHAVIOUR IN BANKRUPTCY RESOLUTION WITH ENDOGENOUS REGRESSORS (Z-SCORE)

Variable (1)	IVModel 1 (2)	IVModel 2 (3)	IVModel 3 (4)	IVModel 4 (5)	IVModel 5 (6)
Correlation (Ω)	**–0.731*****	**–0.571****	**–0.574****	**–0.139**	**–0.141**
FB	**0.581*****	**0.393****	**0.394****	**0.193***	**0.171**
	(2.740)	(2.322)	(2.344)	(1.654)	(1.409)
DIPTA	1.903	1.642	1.614	1.938	1.984
	(1.603)	(1.343)	(1.327)	(1.540)	(1.549)
CEOR	2.223***	2.442***	2.393***	2.473***	2.418***
	(8.008)	(8.494)	(8.301)	(8.381)	(7.818)
CCOM	–1.090***	–1.208***	–1.178***	–1.218***	–1.384***
	(–2.705)	(–3.054)	(–2.787)	(–2.885)	(–2.935)
SALEINT	–0.601*	–0.846***	–0.885***	–1.081***	–1.045***
	(–1.919)	(–2.783)	(–2.821)	(–3.513)	(–3.275)
CEODA	0.571***	0.589***	0.581***	0.567***	0.568***
	(3.949)	(3.942)	(3.915)	(3.807)	(3.626)
INDUSTRY-R	–0.259	–0.445	–0.434	–0.798**	–0.901**
	(–0.720)	(–1.335)	(–1.292)	(–2.416)	(–2.481)
JEXPD	0.480*	0.525**	0.518*	0.671**	0.541**
	(1.797)	(1.991)	(1.899)	(2.513)	(1.962)
PRIMEF	–0.010	–0.041	–0.045	–0.072	–0.059
	(–0.146)	(–0.665)	(–0.716)	(–1.132)	(–0.874)
Constant	–1.115	–0.643	–0.612	–0.152	0.049
	(–1.638)	(–1.082)	(–0.987)	(–0.270)	(0.078)
Log likelihood	–937.96	–880.45	–839.83	–776.11	–702.77
N = 1	257	114	108	100	89
N = 0 + 1	385	248	236	222	202
Overidentifying test Chi2		2.03	1.51	4.78	5.06
Weak instrument tests					
CLR	-	5.54**	5.71**	2.66	1.84
K	-	5.35**	5.55**	2.50	1.70
AR chi2	8.30***	7.73**	7.38*	7.46	6.96
Wald chi2	7.50***	5.39**	5.50**	2.74*	1.98
Observations	385	363	345	323	292

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ (two-sided test). z-statistics in parentheses. 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 2019. Overidentifying test Chi2 is for the Amemiya-Lee-Newey test of overidentifying restrictions. Weak instrument tests: Conditional Likelihood Ratio (CLR) test, Lagrange multiplier K test, the Anderson-Rubin (AR) test statistic and Wald Chi-square test (Finlay *et al.*, 2014).

null hypothesis of orthogonality of the set of instruments with a conventional error of 1%. This assures 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, and the Lagrange multiplier K test (Finlay *et al*., 2014). The results of the CLR and K corroborate the goodness of the models. In these cases, the AR test statistic indicates that the parameters of the endogenous regressors are jointly significant in all the models, except for the IVModel 4 and 5, for which financial benefit is significant at the 0.10 level and insignificant, respectively.

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 ten factors that best explain a firm's likelihood of emerging from Chapter 11 bankruptcy with a within-sample classification accuracy of about 95%. Additionally, we report significant strategic behaviour among Chapter 11 bankruptcy filing firms. The presence of financial benefits 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 11 bankruptcy. Indeed, it seems that 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 light of this result, policymakers may find it appropriate to amend existing bankruptcy laws to discourage such behaviour, or tighten 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, and (iv) requiring debt management programs outside bankruptcy, and so on.

Previous studies show that signals from key external stakeholders contribute to predicting the emergence of bankrupt firms by evaluating bankrupt firms' characteristics more effectively as well as by 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.

REFERENCES

Adler, B. E., V. Capkun, and L. A. Weiss (2013), 'Value Destruction in the New Era of Chapter 11', *The Journal of Law, Economics, and Organization*, Vol. 29, No. 2, Pp. 461–83.

Akerlof, G. A., P. M. Romer, R. E. Hall, and N. G. Mankiw (1993), 'Looting: The Economic Underworld of Bankruptcy For Profit', *Brookings Papers On Economic Activity*, Vol. 2, pp. 1–73.

Altman, E. I. (1968), 'Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy', *The Journal of Finance*, Vol. 23, No. 4, pp. 589–609.

Altman, E. I., E. Hotchkiss, and W. Wang, (2019), *Corporate Financial Distress and Bankruptcy: Predict and Avoid Bankruptcy, Analyze and Invest in Distressed Debt*, John Wiley & Sons, Hoboken, NJ.

Altman, E. I., M. Iwanicz-Drozdowska, E. K. Laitinen, and A. Suvas (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*, Vol. 28, No. 2, pp. 131–71.

Antill, S. (2022), 'Do the Right Firms Survive Bankruptcy?', *Journal of Financial Economics*, 144, No. 2, pp. 523–46.

Aretz, K., S. Banerjee, and O. Pryshchepa (2019), 'In the Path of the Storm: Does Distress Risk Cause Industrial Firms to Risk-Shift?', *Review of Finance*, Vol. 23, pp. 1115–54.

Arora, P. (2018), 'Financially Linked Independent Directors and Bankruptcy Reemergence: The Role of Director Effort', *Journal of Management*, Vol. 44, No. 7, pp. 2665–89.

Aysun, U. (2014), 'Bankruptcy Resolution Capacity and Economic Fluctuations', *Journal of Macroeconomics*, Vol. 40, pp. 387–99.

—— (2015), 'Duration of Bankruptcy Proceedings and Monetary Policy Effectiveness', *Journal of Macroeconomics*, Vol. 44, pp. 295–302.

Barker III, V. L. and P. S. Barr (2002), 'Linking Top Manager Attributions to Strategic Reorientation in Declining Firms Attempting Turnarounds', *Journal of Business Research*, Vol. 55, No. 12, pp. 963–79.

Becker B. and P. Strömberg (2012), 'Fiduciary Duties and Equity-Debtholder Conflicts', *Review of Financial Studies*, Vol. 25, pp. 1931–69.

Boettcher, J., G. Cavanagh, and M. Xu (2014), 'Ethical Issues that Arise in Bankruptcy', *Business and Society Review*, Vol. 119, No. 4, pp. 473–96.

Borenstein, S. and N. L. Rose (2003), 'The Impact of Bankruptcy on Airline Service Levels', *American Economic Review*, Vol. 93, No. 2, pp. 415–19.

Bryan, D. M., S. L. Tiras, and C. M. Wheatley (2002), 'The Interaction of Solvency with Liquidity and its Association with Bankruptcy Emergence', *Journal of Business Finance & Accounting*, Vol. 29, Nos 7–8, pp. 935–65.

Capkun, V. and E. Ors (2021), 'Replacing Key Employee Retention Plans with Incentive Plans in Bankruptcy', *Accounting, Organizations and Society*, Vol. 94, 101278.

Chang, T. and A. Schoar (2006), '*The Effect of Judicial Bias in Chapter 11 Reorganization*', Unpublished Manuscript. Massachusetts Institute of Technology, Cambridge MA.

Choi, S. J., M. Gulati, and E. A. Posner (2013), 'How Well Do Measures of Judicial Ability Predict Judicial Performance? A Case Study Using Securities Class Actions', *International Review of Law and Economics*, Vol. 33, pp. 37–53.

Coordes, L. N. (2015), 'Tthe Geography of Bankruptcy', *Vanderbilt Law Review*, Vol. 68, p. 381.

Dahiya, S., K. John, M. Puri, and G. Ramírez (2003), 'Debtor-in-Possession Financing and Bankruptcy Resolution: Empirical Evidence', *Journal of Financial Economics*, Vol. 69, No. 1, pp. 259–80.

Delaney, K. J. (1999), *Strategic Bankruptcy: How Corporations and Creditors Use Chapter 11 To Their Advantage*, University of California Press, London.

Denis, D. K. and K. J. Rodgers (2007), 'Chapter 11: Duration, Outcome, and Post-reorganization Performance', *Journal of Financial and Quantitative Analysis*, Vol. 42, No. 1, pp. 101.

Donoher, W. J. (2004), 'To File or Not To File? Systemic Incentives, Corporate Control, and the Bankruptcy Decision', *Journal of Management*, Vol. 30, No. 2, pp. 239–62.

Eckbo, B. E. and S. K. Thorburn (2008), 'Automatic Bankruptcy Auctions and Fire-Sales', *Journal of Financial Economics*, Vol. 89, No. 3, pp. 404–22.

Edwards, A., C. Schwab, and T. Shevlin (2016), 'Financial Constraints and Cash Tax Savings', *The Accounting Review*, Vol. 91, No. 3, pp. 859–81.

Ellias, J. A. (2018), 'What Drives Bankruptcy Forum Shopping? Evidence From Market Data', *The Journal of Legal Studies*, Vol. 47, No. 1, pp. 119–49.

Evans, J. and A. L. Borders (2014), 'Strategically Surviving Bankruptcy During A Global Financial Crisis: The Importance of Understanding Chapter 15', *Journal of Business Research*, Vol. 67, No. 1, pp. 2738–742.

Evans III, J. H., S. Luo, and N. J. Nagarajan (2013), 'CEO Turnover, Financial Distress, and Contractual Innovations', *The Accounting Review*, Vol. 89, No. 3, pp. 959–90.

Favara G., E. Morellec, E. Schroth, and P. Valta (2017), 'Debt Enforcement, Investment, and Risk-taking Across Countries', *Journal of Financial Economics*, Vol. 23, pp. 22–41.

Fay, S., E. Hurst, and M. J. White (2002), 'The Household Bankruptcy Decision', *American Economic Review*, Vol. 92, No. 3, pp. 706–18.

Finlay, K., L. Magnusson, and M. Schaffer (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 M. Farid (1991), 'The Intentional Use of Chapter XI: Lingering Versus Immediate Filing', *Strategic Management Journal*, Vol. 12, No. 1, pp. 63–74.

François, P. and A. Raviv (2017), 'Heterogeneous Beliefs and the Choice Between Private Restructuring and Formal Bankruptcy', *The North American Journal of Economics and Finance*, Vol. 41, pp. 156–67.

Franks, J. and O. Sussman (2005), 'Financial Distress and Bank Restructuring of Small to Medium Size UK Companies', *Review of Finance*, Vol. 9, No. 1, pp. 65–96.

Franks, J. and W. Torous (1989), 'An Empirical Investigation of U.S. Firms in Reorganization', *Journal of Finance*, 747–69.

George, T. J. and C. Y. Hwang (2010), 'A Resolution of the Distress Risk. and Leverage Puzzles in the Cross Section of Stock Returns', *Journal of Financial Economics*, Vol. 96, No. 1, pp. 56–79.

Gilje, E. P. (2016), 'Do Firms Engage in Risk-shifting? Empirical Evidence', *The Review of Financial Studies*, Vol. 29, No. 11, pp. 2925–54.

Gilson, S. C. (2010), *Creating Value Through Corporate Restructuring: Case Studies in Bankruptcies, Buyouts, and Breakups*, John Wiley & Sons, Hoboken NJ.

—— (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*, Vol. 24, No. 4, pp. 23–35.

Grant, W. (1994), *Bankruptcy and Insolvency Accounting*, John Wiley & Sons, Hoboken NJ.

Gupta, J. and S. M. Chaudhry (2019), 'Mind the Tail, or Risk to Fail', *Journal of Business Research*, Vol. 99, pp. 167–85.

Gupta, J., A. Gregoriou, and T. Ebrahimi (2018), 'Empirical Comparison of Hazard Models in Predicting SMEs Failure', *Quantitative Finance*, Vol. 18, No. 3, pp. 437–66.

Hainmueller J. (2012), 'Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies', *Political Analysis*, Vol. 20, No. 1, pp. 25–46.

Hainmueller, J. and Y. Xu (2013), 'Ebalance: A Stata Package For Entropy Balancing', *Journal of Statistical Software*, Vol. 54, No. 7, pp. 1–18.

Hillegeist, S. A., E. K. Keating, D. P. Cram, and K. G. Lundstedt (2004), 'Assessing the Probability of Bankruptcy', *Review of Accounting Studies*, Vol. 9, No. 1, pp. 5–34.

Hosmer Jr, D. W., S. Lemeshow, and R. X. Sturdivant (2013), *Applied Logistic Regression*, John Wiley & Sons, Hoboken NJ.

Ivashina, V., B. Iverson, and D. C. Smith (2016), 'The Ownership and Trading of Debt Claims in Chapter 11 Restructurings', *Journal of Financial Economics*, Vol. 119, No. 2, pp. 316–35.

James, S. D. (2016), 'Strategic Bankruptcy: A Stakeholder Management Perspective', *Journal of Business Research*, Vol. 69, No. 2, pp. 492–99.

Jensen M. C. and W. H. Meckling (1976), 'Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure', *Journal of Financial Economics*, Vol. 3, pp. 305–60.

Jiang, H., A. A. Cannella Jr, J. Xia, and M. Semadeni (2017), 'Choose to Fight or Choose to Flee? A Network Embeddedness Perspective of Executive Ship Jumping in Declining Firms', *Strategic Management Journal*, Vol. 38, No. 10. pp. 2061–79.

Jones, S. (2017), 'Corporate Bankruptcy Prediction: A High Dimensional Analysis', *Review of Accounting Studies*, Vol. 22, pp. 1366–422.

Koh, S., R. B. Durand, L. Dai, and M. Chang (2015), 'Financial Distress: Lifecycle and Corporate Restructuring', *Journal of Corporate Finance*, Vol. 33, pp. 19–33.

Lehavy, R. (2002), 'Reporting Discretion and the Choice of Fresh Start Values in Companies Emerging From Chapter 11 Bankruptcy', *Review of Accounting Studies*, Vol. 7, No. 1, pp. 53–73.

Li, K. and W. Wang (2016), 'Debtor-in-Possession Financing, Loan-to-Loan, and Loan-to-Own', *Journal of Corporate Finance*, Vol. 39, pp. 121-138.

Li, N., Y. Lou, C. A. Otto, and R. Wittenberg-Moerman (2021), Accounting Quality and Debt Concentration', *The Accounting Review*, Vol. 96, No. 1, pp. 377–400.

Li, Y. (2013), 'A Nonlinear Wealth Transfer fom Shareholders to Creditors Around Chapter 11 Filing', *Journal of Financial Economics*, Vol. 107, No. 1, pp. 183–98.

Long, J. S. and J. Freese (2014), *Regression Models For Categorical Dependent Variables Using Stata*, Stata Press, Texas.

Lopucki, L. M. (2006), *Courting Failure. How Competition For Big Cases Is Corrupting the Bankruptcy Courts*, University of Michigan Press, Ann Arbor.

Lopucki, L. M. and J. W. Doherty (2015), 'Bankruptcy Survival', *UCLA Law Review*, Vol. 62, p. 969.

Maskara, P. K. and L. S. Miller (2018), 'Do Golden Parachutes Matter? Evidence From Firms that Ultimately Filed for Bankruptcy', *The Quarterly Review of Economics and Finance*, Vol. 67, pp. 63–78.

Monsen, B. R. (2022), 'The Determinants and Consequences of Big 4 Lobbying Positions on Proposed Financial Accounting Standards', *The Accounting Review*, Vol. 97, No. 3, pp. 309–41.

Moulton, W. N. and H. Thomas (1993), 'Bankruptcy as a Deliberate Strategy: Theoretical Considerations and Empirical Evidence', *Strategic Management Journal*, Vol. 14, No. 2, pp. 125–35.

Pierk, J. (2021), 'Big Baths and CEO Overconfidence', *Accounting and Business Research*, Vol. 51, No. 2, pp. 185–205.

Reboul, J. and A. Toldrà-Simats (2016), 'The Strategic Behavior of Firms With Debt', *Journal of Financial and Quantitative Analysis*, Vol. 51, No. 5, pp. 1611–36.

Sarkar, S. and O. Osiyevskyy (2018), 'Organizational Change and Rigidity During Crisis: A Review of the Paradox', *European Management Journal*, Vol. 36, No. 1, pp. 47–58.

Shroff, N., R. S. Verdi, and B. P. Yost (2017), 'When Does the Peer Information Environment Matter?', *Journal of Accounting and Economics*, Vol. 64, Nos 2–3, pp. 183–214.

Smith Jr, C. W. (1993), 'A Perspective on Accounting-based Debt Covenant Violations', *The Accounting Review*, Vol. 68, No. 2, pp. 289–303.

Sutton, R. I. and A. L. Callahan (1987), 'The Stigma of Bankruptcy: Spoiled Organizational Image and its Management', *Academy of Management Journal*, Vol. 30, No. 3, pp. 405–36.

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*, Vol. 23, p. 571.

Trahms, C. A., H. A. Ndofor, and D. G. Sirmon (2013), 'Organizational Decline and Turnaround: A Review and Agenda for Future Research', *Journal of Management*, Vol. 39, No. 5, pp. 1277–307.

US Court (2022), *Chapter 11 – Bankruptcy Basics*, Retrieved From: https://Www.Uscourts.Gov/Services-Forms/Bankruptcy/Bankruptcy-Basics/Chapter-11-Bankruptcy-Basics [Accessed 4 November 4 2022].

Xia, J., D. D. Dawley, H. Jiang, R. Ma, and K. B. Boal (2016), 'Resolving a Dilemma of Signaling Bankrupt-Firm Emergence: A Dynamic Integrative View', *Strategic Management Journal*, Vol. 37, No. 8, pp. 1754–64.

Yu, K. and D. He (2018), 'The Choice Between Bankruptcy Liquidation and Bankruptcy Reorganization: A Model and Evidence', *Journal of Management Analytics*, Vol. 5, No. 3, pp. 170–97.

Zhang, S., T. Sabarwal, and L. Gan (2015), 'Strategic or Nonstrategic: The Role of Financial Benefit in Bankruptcy', *Economic Inquiry*, Vol. 53, No. 2, pp. 1004–18.

Zwiebel, J. (1996), 'Dynamic Capital Structure Under Managerial Entrenchment', *The American Economic Review*, Vol. 86, No. 5, pp. 1197–215.

APPENDIX A

SAMPLING PROCEDURE

Sampling Steps	Number of Observations
Initial number of firms in Lopucki Database	1,163
Excluded Chapter 7 cases	(25)
Excluded cases where *EMERGE* is missing	(40)
Excluded cases with missing GVKEY (required to merge with the Compustat database)	(61)
Excluded cases before 1994 because *SALEINT* is not available before that period.	(204)
Excluded due to being in Transportation, Communications, Electric, Gas & Public Utilities, Finance, Insurance & Real Estate, and Public Administration.	(250)
Excluded due to the absence of financial information in either current, past, or prior 2 years.	(9)
Final Sample for the Baseline Multivariate Model (See Table 5)	**574**

APPENDIX B

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	*TLTA*	Ratio of total liabilities to total assets before filing bankruptcy.	LiabBefore/ AssetsBefore
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*	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	DipAtty

(Continues)

No.	Characteristic Group	Variable	Description	BRD Name
			represented the DIP in filing of the bankruptcy case), or the Attorney has handled before this case.	
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 reorganization (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 US Trustee appointed a creditors' committee to represent the unsecured creditors prior to case disposition, and 0 otherwise.	CommCred
15	Case	*DIPL*	Dummy variable equalling 1 if the court approved DIP borrowing outside the ordinary course of business, and 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, categorized 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	HeadCourtCityToDE

(Continues)

No.	Characteristic Group	Variable	Description	BRD Name
			debtor's case has been assigned (HeadCourtCity) to Wilmington, DE, measured as the crow flies.	
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, and 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

APPENDIX C

DESCRIPTIVE STATISTICS

	Non-Emerging (*EMERGE* = 0)					Emerging (*EMERGE* = 1)				
Variable	Mean	Median	S.D.	Min	Max	Mean	Median	S.D.	Min	Max
CSIZE	6.78	6.54	0.88	5.58	9.45	7.02	6.82	0.98	5.59	11.6
TLTA	0.86	0.84	0.32	0.1	2.29	1.12	0.98	0.59	0.25	5.68
PEBIT	0.41	0	0.49	0	1	0.56	1	0.5	0	1
EMP	7.81	7.84	1.54	3.71	11.58	8.1	8.21	1.55	0	12.44
INDUSTRY-R	0.25	0	0.43	0	1	0.13	0	0.33	0	1
INDUSTRY-M	0.36	0	0.48	0	1	0.46	0	0.5	0	1
JEXP	1.26	1.1	1.2	0	3.93	1.62	1.61	1.22	0	3.95
JEXPD	0.32	0	0.47	0	1	0.48	0	0.5	0	1
AEXP	1.41	1.1	1.31	0	4.19	1.89	1.79	1.38	0	4.23
CEOR	0.21	0	0.41	0	1	0.81	1	0.39	0	1
CEODA	0.68	0.47	0.67	0	4.04	1.67	1.13	1.91	0	12.67
SALEINT	0.51	1	0.5	0	1	0.15	0	0.35	0	1
PREAGR	0.12	0	0.33	0	1	0.47	0	0.5	0	1
DURATION	1.58	1.18	1.49	0.04	12.24	1.08	0.73	1.24	0.06	10.84
CCOM	0.95	1	0.21	0	1	0.76	1	0.43	0	1
CFILE	0.48	0	0.5	0	1	0.33	0	0.47	0	1
HCCTODE	6.47	6.68	1.1	3.33	7.83	6.28	6.48	1.19	0	7.83
BSHOP	0.65	1	0.48	0	1	0.77	1	0.42	0	1
DIPL	0.27	0	0.45	0	1	0.43	0	0.5	0	1
DIPTA	0.04	0	0.11	0	0.66	0.09	0	0.15	0	1.01
PRIME1	6.62	7.75	2.28	3.25	9.5	5.86	5.25	2.19	3.25	9.5
PRIMEF	5.94	5.5	2.24	3.25	9.5	5.38	4.75	2.21	3.25	9.5

APPENDIX D

LASSO AND STEPWISE REGRESSION ESTIMATES

	LASSO			Stepwise		
	Coefficient	Standard Error	AME in %	Coefficient	Standard Error	AME in %
Variable	(2)	(3)	(4)	(5)	(3)	(4)
CEOR	4.999*** (10.154)	0.492	35.20	5.006*** (10.371)	0.482	35.30
CEODA	1.691*** (5.937)	0.284	11.90	1.618*** (5.973)	0.271	11.41
PREAGR	1.477*** (2.977)	0.496	10.40	1.586*** (3.190)	0.497	11.18
SALEINT	–0.974** (–2.413)	0.403	–6.85	–0.947** (–2.513)	0.376	–6.67
PRIME1	–0.093 (–0.799)	0.115	–0.65			
DURATION	–0.482*** (–3.739)	0.128	–3.39	–0.467*** (–3.895)	0.120	–3.29
BSHOP	0.215 (0.524)	0.410	1.51			
CCOM	–1.402** (–2.005)	0.699	–9.87	–1.601** (–2.290)	0.699	–11.29
DIPL	–0.026 (–0.050)	0.514	–0.17			
DIPTA	2.562 (1.404)	1.824	18.03	3.720*** (2.677)	1.389	26.23
TLTA	0.886** (2.002)	0.442	6.23	1.071** (2.349)	0.456	7.55
EMPB	0.020 (0.176)	0.116	0.14			
JEXP	0.312* (1.808)	0.172	2.19			
INDUSTRY-M	–0.331 (–0.886)	0.330	–			
INDUSTRY-S	0.117 (0.234)	0.500	–			
AEXP	0.196 (1.446)	0.135	1.38	0.265* (1.947)	0.136	1.86
PEBIT	0.297 (0.907)	0.327	2.09			
PRIMEF	–0.078 (–0.699)	0.111	–0.54			
lnHCCTODE				0.392*** (2.601)	0.150	2.76
JEXPD				0.828** (2.255)	0.367	5.83

(Continues)

	LASSO			Stepwise		
	Coefficient	Standard Error	AME in %	Coefficient	Standard Error	AME in %
Variable	(2)	(3)	(4)	(5)	(3)	(4)
Constant	–2.695*			–5.957***		
	(–1.926)			(–4.043)		
Log likelihood	–131.91			–129.80		
LR Chi2	440.67			434.29		
Pseudo R^2	0.6255			0.6259		
AUROC-W	0.9616			0.9612		
AUROC-H	0.8852			0.9164		
N = 1	397			389		
N = 0 + 1	572			562		

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ (two-sided test). z-statistics in parentheses.