What factors influence the success of a Chapter 11 filing?

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Abstract

Kathrin Pampel – What factors influence the success of a Chapter 11 filing?

It is vital for a modern economy to have an efficient bankruptcy procedure in place to ensure stability and resilience. In the U.S., Chapter 11 offers firms a legal framework for reorganization. However, outcomes vary from case to case. While some companies emerge successfully others are forced to liquidate or refile shortly after emergence. This leads to the question: **What factors influence the success of a Chapter 11 filing?**

To answer this question, I analysed a dataset of large public U.S. bankruptcy filings between 1980 to 2021. I created three binary success measures to capture different dimensions of success: 'Emergence From Chapter 11', 'No Refiling Within 5 Years' and 'EBITDA Sign Change'. For my independent predictors I used a broad set of variables capturing financial health, industry conditions, procedural characteristics and governance and legal features.

The analysis revealed that success is not a uniform concept. The use of DIP financing, CEO replacement and filing in Delaware or New York increases the likelihood of emergence, while free-fall cases and cases that include asset sales are less likely to emerge. Moreover, larger companies and those that file as a free-fall are less likely to refile within 5 years. Filing in Delaware or New York on the other hand, increases the probability of refiling. Finally, industry distress at emergence lowers the probability of a company to turn a negative EBITDA positive, while cases with a creditor's committee in place are much more likely to turn a negative EBITDA positive.

Keywords: Chapter 11, corporate bankruptcy, bankruptcy outcome, reorganization, DIP financing, CEO turnover, free-fall, refiling risk, financial distress.

Resumo

Kathrin Pampel - Quais fatores influenciam o sucesso de um pedido de recuperação judicial conforme o Capítulo 11?

É vital para uma economia moderna dispor de um processo de falência eficiente, a fim de garantir a estabilidade e a resiliência. Nos EUA, o Capítulo 11 oferece às empresas um enquadramento legal para a sua reorganização. No entanto, os resultados variam de caso para caso. Enquanto algumas empresas conseguem reerguer-se com êxito, outras são forçadas a liquidar ou a registar-se novamente pouco tempo depois de emergirem. Isto levanta a questão: que fatores influenciam o êxito de um pedido ao abrigo do Capítulo 11?

Para responder, analisei grandes pedidos públicos de falência nos EUA entre 1980 e 2021. Criei três medidas binárias de sucesso para capturar diferentes dimensões: 'Emergência do Capítulo 11', 'Não refilmagem dentro de 5 anos' e 'Mudança de sinal de EBITDA'. Para os preditores independentes, utilizei um vasto conjunto de variáveis que captam a saúde financeira, as condições do setor, as caraterísticas processuais e jurídicas.

A análise revelou que o sucesso não é uniforme. O uso de financiamento DIP, a substituição do CEO e o registo em Delaware ou Nova Iorque aumentam a probabilidade de emergência. Já os casos de queda livre e os que envolvem venda de ativos apresentam menor probabilidade. Empresas maiores e em processo de falência têm menor chance de evitar refilmagem em 5 anos, enquanto o registo em Delaware/Nova Iorque aumenta essa probabilidade. Por fim, dificuldades setoriais reduzem a melhoria do EBITDA, ao passo que a presença de um comité de credores aumenta significativamente essa probabilidade.

Palavras-chave: Capítulo 11, falência empresarial, resultado da falência, reorganização, financiamento DIP, substituição de CEO, queda livre, risco de refilmagem, dificuldade financeira.

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1. Introduction

Having efficient corporate bankruptcy procedures in place is a cornerstone for any modern economy, as they offer distressed firms a second chance to reorganize. This is critical to achieve economic growth, preserve jobs and avoid nation-wide economic crises. Cases such as the fall of Lehman Brothers in 2008, which triggered widespread panic and a global liquidity freeze, illustrate the profound and far-reaching impact of bankruptcy processes (Ayotte & Skeel, 2013). In the U.S. Chapter 11 of the Bankruptcy Code provides a legal framework on the reorganization of distressed firms. Even though the use of the framework is widespread, and Chapter 11 underwent many changes to enhance the bankruptcy procedure since its adaption in 1978, the outcomes of the filing vary substantially across firms. While some companies emerge from Chapter 11 stronger, other companies relapse into financial distress only a few years after emerging. Some do not even overcome the hurdle of emergence and liquidate instead. This raised a central question that continues to attract attention from scholars: **What factors influence the success of a Chapter 11 filing?**

Understanding these drivers is of significant practical importance, particularly for policymakers, creditors and debtors. Identifying factors that drive the outcome of bankruptcies helps policymakers to refine the legal framework, enables creditors to reliably assess risk and recovery expectations and supports debtors not only to efficiently reorganize in case of bankruptcy but also to prepare for potential distress beforehand. On a broader scale, everyone that participates in economic activities, such as employees, suppliers and investors, benefits from improved bankruptcy outcomes.

This thesis makes several contributions to existing literature on U.S. bankruptcies. First, I detected a lack of recent empirical studies on Chapter 11 outcomes. The dataset used in this thesis spans from 1980 to 2021 and includes all major public U.S. filings during the period. This allowed me to capture evolving trends, which is crucial in the ever-changing bankruptcy environment. Secondly, while scholars have defined many different measures to assess Chapter 11 success, most studies tend to only focus on emergence. To offer a more comprehensive understanding of short-term and long-term outcomes of Chapter 11 filings I decided to add two measures to the traditional emergence variable and constructed two binary indicators which analyse if the company refiled within five years of emergence and if the company was able to achieve a positive EBITDA sign change. Moreover, I use a very broad set of independent predictor variables capturing financial health, industry conditions, procedural characteristics and governance and legal features. Finally, by measuring key financial indicators pre-filing and at emergence, I ensure that the values used are contextually relevant for the specific success measures.

My results indicate that the predictive power of the factors and the direction of the relationship depends on the chosen measure of success. The key results are the following: 1. Firm size positively influences the likelihood of avoiding refiling within five years of emergence. 2. Companies that are highly levered have a higher probability of emerging but tend to refile. 3. Companies with higher ROA are significantly more likely to emerge. 4. Higher tangibility of assets increases the likelihood of emergence. 5. Industry distress at emergence lowers the probability of a company to turn a negative EBITDA positive. 6. Companies that receive DIP financing have a much higher likelihood to emerge. 7. Duration is negatively related with emergence. 8. Free-fall cases are significantly less likely to emerge from Chapter 11, but if they emerge, they have a much higher likelihood of avoiding refiling. 9. Companies that engage in asset sales during the reorganisation are much less likely to emerge. 10. Changing the CEO during the reorganization process heavily increases the probability of emergence. 11. Cases with a creditor's committee in place are much more likely to turn a negative EBITDA positive. 12. Companies that file in Delaware or New York have a slightly higher probability of emerging but are significantly more likely to refile.

The remainder of this thesis is structured as followed: First, an extensive literature review is provided which outlines the general process and evolution of Chapter 11, summarizes existing success measures and outlines key findings from prior studies. This is followed by a description of the used datasets and the methodology section which describes how key variables were created. Afterwards, descriptive statistics are provided and 4 cases from the dataset are discussed. Then next section focuses on the regression analysis and outputs, which is then followed by a detailed result discussion and a paragraph on robustness checks. Finally, the last section concludes with a summary of the most important findings and their policy implications, as well as limitations and directions for future research.

2. Literature review

2.1. Chapter 11 – overview

Chapter 11 and Chapter 7 were adopted as part of the Bankruptcy Reform Act in 1978. While Chapter 7 enables the distressed firms to file for liquidation, during which a court appointed trustee organizes the sale of the debtors' assets of which the proceeds are used to pay back the creditors according to their recovery priority, Chapter 11 filings are considered a corporate reorganization (United States Courts, n.d.). Chapter 11 enables firms to continue its business operations during the reorganisation process and expects the firm to continue operating after leaving bankruptcy (as a going concern). Furthermore, after filing the distressed company immediately gets protected through an **automatic stay** which halts all interest and principal payments to creditors and prevents creditors from seizing their collateral. This creates time for the debtor to reorganize and renegotiate solutions for the financial situation (Hotchkiss et al. 2008).

Usually, the existing management remains in control of running the business as the **Debtor-in-Possession** (DIP) under court oversight (Hotchkiss et al. 2008). While management continuous to make operational decisions, court approval is needed for significant financial decisions. In a few extreme cases such as situations including "fraud, dishonesty, incompetence, gross mismanagement, or if such appointment is in the interest of creditors, any equity security holders and other interests of the estate" a case trustee gets appointed (United States Courts, n.d.). In this case the trustee is responsible for running the debtor's business, managing its property and can file a reorganization plan. The trustee's appointment may be terminated at any point by the court to restore the DIP. In any case a **U.S. Trustee** is appointed to monitor the bankruptcy case and enforce compliance (United States Courts, n.d.).

To represent and protect unsecured creditors the U.S. Trustee appoints a **Creditors' Committee** in many reorganizations. This committee usually consist of the distressed firms' seven largest unsecured creditors. The Creditors' Committee acts as a watchdog that monitors, consults and investigates the DIP. Furthermore, the U.S. Trustee can appoint additional committees to represent the interests of other claimholder classes (Harner & Marincic, 2011).

For the first 120 days (possibility to extend to 18 months) after the Chapter 11 filing, the debtor has the exclusive right to submit a **plan for reorganization**, which may include a fundamental operational restructuring. Among other things, the reorganization plan must also categorize claims into classes and interests for treatment and specify the compensation of each class based on their pre-bankruptcy claim, which is usually distributed as a combination of equity, new debt and cash (Hotchkiss et al. 2008). The court must confirm that the plan is feasible, proposed in good faith and complies with the Bankruptcy Code. The plan needs to be accepted by the creditors within 180 days (possibility to extend to 20 months) of the petition filing date. If these deadlines are not met other parties of interest can propose a plan (Administrative Office of the U.S. Courts, n.d.).

"*An entire class of claims is deemed to accept a plan if the plan is accepted by creditors that hold at least two-thirds in amount and more than one-half in number of the allowed claims in the class. […] if there are impaired classes of claims, the court cannot confirm a plan unless it has been accepted by at least one class of non-insiders who hold impaired claims […]. [H]olders of unimpaired claims are deemed to have accepted the plan*" (Administrative Office of the U.S. Courts, n.d.).

To address the reluctance of lenders to provide additional loans needed for the reorganization due to repayment uncertainty, the Bankruptcy Code gives special rights to post-petition lenders (Dahiya et al., 2003). Lenders who finance a company under Chapter 11 are also called **DIP lenders**. They are granted the highest priority of unsecured claims (administrative-expense priority), which means that their claims are senior to all existing unsecured debt. This is in contrast to normal contract law outside bankruptcy, where one unsecured creditor cannot jump ahead of another without consent (Ayotte & Skeel, 2013). In most cases DIP financing is provided by a company's pre-bankruptcy senior creditors, rather than outside investors. This is the case because the Bankruptcy Code makes it hard for new lenders to outrank existing senior creditors. Furthermore, existing creditors can control the direction of the bankruptcy without needing to get formal reorganisation plan approval by embedding preferred deal terms into the DIP loan contract (Ayotte & Ellias, 2003). Normally, the DIP loans must be paid off entirely for the company to be able to emerge from Chapter 11 (Dahiya et al., 2003). In general, a company emerges from Chapter 11 after the reorganisation plan is confirmed and put into action (Administrative Office of the U.S. Courts, n.d.).

2.2. The evolution of Chapter 11

Since the Bankruptcy Codes adoption in 1978, there have been quite a few changes in legislation as well as the general environment surrounding bankruptcies in the U.S. A major change in legislation was the **Bankruptcy Amendments and Federal Judgeship Act of 1984,** which reconstituted Bankruptcy courts as units of the U.S. district courts. This had major implications because since then bankruptcy judges can only decide on core proceedings (e.g., confirmation of plans and counterclaims), while for non-core proceedings that are just related to the bankruptcy case (e.g., state law contract claims) a district court judge needs to review the findings. Hence, bankruptcy judges are under the oversight of district court judges (Countryman, 1985).

The **Bankruptcy Reform Act of 1994** made targeted improvements to the 1978 Bankruptcy Code, particularly within Chapter 11 and laid the foundation for later reforms. One key change was regarding professional fees and disclosure. The act states that the U.S. Trustee must review requests for professional service compensation and check if they are reasonable and justified. Hence, the U.S. Trustee's authority was further increased. The reform also strengthened the Chapter 11 plan confirmation standards of feasibility and to act in the best interest of creditors. Another important change was the small business provision. The act states that small businesses (defined as businesses with debt below $2mn) can reorganize without the need to form a creditor committee, have a shortened exclusivity period and can combine disclosure and confirmation hearings to speed up the process (U.S. Congress, 1994).

The most significant legislative reform in recent decades is the **Bankruptcy Abuse Prevention and Consumer Protection Act of 2005** (BAPCPA). On top of tougher eligibility rules and increased costs, one major change was that the exclusivity period for all debtors was shortened to a maximum of 18 months and the period to gain acceptance to 20 months. Prior to the Reform, there was no official limit for the exclusivity period. The BAPCPA also implemented caps on management compensation (Miller & Waisman, 2005).

It does not come as a surprise that with the many changes in legislation, the general environment surrounding Chapter 11 filings changed. One major trend observed by Hotchkiss et al. (2023) is that **capital structures of companies that enter reorganisation are becoming more complex**. They are often dominated by first-lien secured lender with many firms already having given secured creditors claims on almost all their assets before filing for Chapter 11. This has led to significant control on the outcome of the reorganisation being given to first-lien lenders, especially when their secured debt exceeds the firm value. Additionally, the ongoing growth of the syndicated loan market, which is largely fuelled by an increasing market share of nonbank lenders, has added more layers and variability of debt claims. This further complicates the reorganisation (Hotchkiss et al., 2023). Moreover, LoPucki (2015) found that there has been a significant increase in pre-bankruptcy leverage levels.

DIP lenders have gradually strengthened their control in Chapter 11. Today it is not unusual that DIP loan agreements predetermine the outcome and direction of the reorganisation. This is also reflected in a **shift from management-controlled to creditor-supervised bankruptcies** which have been observed since the early 2000s. Ayotte and Ellias (2022) "describe this transaction—when management agrees to transfer control over the bankruptcy process to a subset of the company's creditors at the very beginning of Chapter 11 in exchange for compensation—as a 'bankruptcy process sale'." Moreover, the percentage of DIP loans that were designed to fund a specific outcome has increased from 10% in 1995 to 57% in 2015. The DIP loans nowadays give creditors significant control as they dictate who gets paid, block alternative restructuring options and protect themselves from lawsuits (Ayotte and Ellias, 2022). On top of the shift in judicial attitude towards approving creditor-friendly DIP financing terms, courts also increasingly approved liquidations even if this implies a zero recovery for pre-bankruptcy shareholders since the early 2000s (Adlera et al., 2013).

The shift towards creditor control has also been reinforced by a change **Uniform Commercial Code (UCC)**, which also became prominent in the early 2000s (Adlera et al., 2013). While the UCC is not part of the Bankruptcy Code it still very relevant to bankruptcies. The UCC provides rules and regulation for commercial transactions across U.S. states. While the UCC is not federal law, all of the 50 states have adopted it in some form, ensuring consistency in commercial law nationwide (Legal Information Institute, n.d.-a). Article 9 deals with secured transaction and the creation and enforcement of security interest in personal property. Hence, the article determines which creditors have priority over a debtor's assets (Legal Information Institute, n.d.-b). In 2001 UCC §9-104 was adopted, which allows lenders to take security interests in a debtor's bank account, giving them direct control over the distressed company's cash. This means, that since 2001 many companies that enter Chapter 11 have no access to their own operating capital and are fully dependent on the dominant debtor who controls liquidity (Adlera et al., 2013).

Some companies have already established an informally settled plan before they file for bankruptcy, which can be divided into three levels: **prepackaged (prepacks), pre-negotiated and free fall** (LoPucki and Doherty, 2015). Prepacks refer to cases in which votes on a legally binding reorganisation plan are taken prior to filing, which reduces uncertainty and increases the probability to reorganize successfully (Hotchkiss et al., 2023). In a pre-negotiated bankruptcy, the debtor prepares a plan term sheet and secures the agreement of at least one key creditor. If neither of those two arrangements exist, the filling is classified as a free fall (LoPucki and Doherty, 2015). Hotchkiss et al. (2023) also discovered a **decrease in the duration** of bankruptcies between 2000 and 2020. While in 2000 many companies spend over 2 years in bankruptcy protection, the average in 2020 was 103 days. The authors argue that an increase in prepackaged **bankruptcies (prepacks), which now represent a significant share of filings**, contribute to this shorter duration. This is because companies that file for Chapter 11 with prepacks spend less time to reorganize (Tashjian et al. 1994).

Moreover, there has been a **strong increase in Restructuring Support Agreements (RSAs)** in recent years. RSAs refer to reorganisation plans thar are drafted with a company's key creditors before filing for bankruptcy. Those creditors contractually agree to support the plan. The agreements often include aspects such as management incentives, DIP financing and asset purchase agreements. RSAs used to be rather uncommon and have started to gain in popularity since the mid-2000s. In 2004 around 20% of large bankruptcies, with assets of more than $100mn, used RSAs. This number climbed to nearly 50% in 2020. RSAs typically involve secured creditors but in recent years PE sponsors and other equity owners have been involved in the agreements as well. In general, RSAs help to coordinate key parties and provide a structured and less costly path out of bankruptcy, with higher recovery probabilities. However, RSAs might also incentivize opportunistic behaviour seeking to improve their own recoveries at the expense of others (Hotchkiss et al., 2023).

Hotchkiss et al. (2023) also reported an **increase in 363 sales**, which refer to asset sales outside the ordinary course of business which are regulated by section 363 of the U.S. Bankruptcy Code. For public US companies these cases have increased from 12% in 2000 to 34% in 2021. The trend is even stronger among smaller and private firms. Courts used to be quite reluctant to permit these sales because they do not require approval through a full creditor vote. However, courts have become more comfortable with the approach of using Chapter 11 to sell entire firms as more and more cases are getting accepted. On top of avoiding a lengthy and costly Chapter 11 process, another key benefit of 363 Sales is that assets are sold clear of most liabilities (e.g. pension obligations) and free. Additionally, the sale process is court-approved which makes future legal challenges less likely. Hence. They offer a quick sale alternative to traditional reorganisation. However, critics argue that Section 363 undermines creditor rights, especially of junior creditors who have no say. Furthermore, if 363 Sales are rushed, they might lead to fire-sale prices at the expense of more junior creditors (Hotchkiss et al., 2023).

Furthermore, there has been a strong **decline in CEO turnover during and shortly after bankruptcies** since the 1980s**.** According to LoPucki (2015) "chapter 11 [today is] much more a safe harbour for the managers of large public companies than it was three decades ago."

2.3. Success measures

Before diving deeper into the various ways of how scholars define success of Chapter 11 it is important to understand the different outcomes of a Chapter 11 process. Overall, there are four outcomes that mark the termination of a Chapter 11 case. A case can be dismissed by the court for example, because the debtor and creditors achieved a private agreement. Secondly, the case might be converted into a Chapter 7 liquidation. Another option is a liquidation by sale under Chapter 11 (such as a 363 sale). The final potential outcome is the reorganisation plan confirmation by the court (Warren and Westbrook, 2009). The latter is also the starting point for LoPucki's (2015) attempt to measure success.

In total LoPucki (2015) definiens nine operational measures for success rather than a single definition. His first measure, **(1) plan confirmation**, stamps from Warren and Westbrook's (2009) argument that plan confirmation by the court is an essential milestone in a Chapter 11 process as it is the core objective of the system. It reflects the confidence of both the creditors and the court on the future of the company. However, LoPucki (2015) also warns that plan confirmation as a success measure is potentially incomplete and misleading as it does not reflect the actual execution of the plan and the long-term survival. The author concludes that "plan confirmation predicts future success, not that confirmation is that success" (LoPucki, 2015).

(2) Entity survival is the second measure mentioned by LoPucki (2015), which he defines as the survival of either the operating company or the legal entity that holds tax benefits (tax net operating losses; NOLs). This approach recognizes that businesses may be kept alive purely for financial or tax-related reasons (e.g. offsetting the NOLs against the income of an acquired company). However, a change in tax laws made this use of NOLs obsolete. Therefore, this measure of success is no longer meaningful (LoPucki, 2015).

“[T]he primary goal of Chapter 11 is to enable a debtor to restructure his business so as to be able to continue operating” and “[t]he fundamental purpose of reorganization is to prevent a debtor from going into liquidation, with an attendant loss of jobs and possible misuse of economic resources” (NLRB v. Bildisco & Bildisco, 1984). This makes **(3) business survival** an essential measure of success, even though some scholars contend that liquidation is better in some cases if it provides greater returns to creditors and shareholders. Furthermore, LoPucki (2015) argues that only if the core business remains unified within a single entity throughout the process, the business truly survives. Which makes it extremely complex to measure as detailed case information would be needed. Hence, he defines survival in a broader and more flexible measure. A company is considered to survive if any part of it continues to operate as an independent business, even if it was acquired (as long as it operates separately). This implies that a company also survives if it is being sold through a Section 363 sale or as part of a confirmation plan. However, a company does not survive if it is fully merged into another business (LoPucki, 2015). This is also the definition LoPucki and Doherty (2015) use in their paper to analyse which factors influence the likelihood of succeeding in a bankruptcy reorganisation (also called emerge).

The **(4) proportion-of-business surviving** measures how much of the business survives. LoPucki (2015) expresses that in terms of the percentage of a company’s assets before the reorganisation to post-reorganisation. He argues, that the greater the proportion of assets of the emerging company, the more successful the reorganisation process was.

Then LoPucki (2015) defines measures for financial and economic success next measure of success as **(5) leverage emerging**, **(6) operating income** and the **(7) refiling rate**. The primary goal of a restructuring process should be to reduce leverage to a debt-to-asset ratio that the debtor can financially sustain. Furthermore, attaining a positive operating income is commonly regarded as a successful reorganisation. LoPucki (2015) uses two EBIT-based measures to quantify the operating income success. First, he measures the directional change by analysing if the EBIT increased or decreased during the restructuring process (time frame: last 10-K before bankruptcy to first 10-K after bankruptcy). Secondly, he analyses if there was a sign change in the EBIT. Regarding the refiling indicator, it is important to note that LoPucki (2015) defines refiling success as companies that have not refiled for bankruptcy within five years of emergence, as later re-filings are likely to be unrelated to the initial Chapter 11 reorganisation.

With respect to refiling, LoPucki (2015) mentions that re-filings that occur more than five years post emergence are likely due to reasons unrelated to the initial Chapter 11 filing.

The next measure of success is the **(8) CEO turnover**, which is intended to analyse the impact of Chapter 11 on improvements in the management of the distressed company through changes in executive leadership. CEO turnover can be constructed as a change in CEO during the bankruptcy or an additional component of a change during the ninety days following emergence can be added (LoPucki, 2015). LoPucki's (2015) final measure of success is the **(9) shareholder retention of control**. However, this measure is very difficult to track, which is why the author drops it.

Altman (2009) and Hotchkiss et al. (2008) have a more focused approach to success which is about the overall outcome of the Chapter 11 filing. Hotchkiss et al. (2008) define success as **reaching an agreement** which he describes as some kind of reorganisation plan. It is important to note, that liquidation as an outcome should not be considered successful. Altman (2009) has a similar view but for him it is essential, that for a case to be successful there should not only be a plan confirmation, but the company actually needs to **emerge as a going concern**, operating independently. This also implies that the company needs to be reorganised not liquidated. This definition is more or less in line with LoPucki's (2015) business survival approach. Additionally, Altman (2009) also mentions the importance of **refiling** as an indicator. More specifically he states, "[T]he most extreme instance of a failed Chapter 11 is that the reorganized company files for bankruptcy again—a situation that has been described as 'Chapter 22'" (Altman, 2009).

Both Altman (2009) and Hotchkiss et al. (2008) also suggest adding a measure that captures **performance post-bankruptcy**. On top of analysing operating performance as suggested by LoPucki (2015) the authors also mention factors such as profitability and returns.

2.4. Factors that influence the outcome of a Chapter 11 process

Li and Wang (2016) show that **ROA (return on assets)** is a significant and positive predictor of emergence success in Chapter 11. They argue that a strong operating performance enables companies to execute viable reorganization plans and reflects underlying business viability, which is critical for creditors confidence. As a result of that, companies with higher ROA are more likely to receive DIP financing. Distressed companies that receive **DIP financing** have a higher probability of successfully emerging from Chapter 11 than being liquidated (Carapeto, 2003). This observation even holds when controlling for firm size, leverage, asset composition and industry as shown by Dahiya et al., (2003). "These results are consistent with DIP lenders having an information role, playing a screening role in which they are able to identify distressed firms that are strong and likely to emerge quickly, as well as a monitoring role in which the DIP lenders help firms to emerge quickly" (Dahiya et al., 2003). On top of that, the reorganisation period, time to emerge as well as their time to liquidation (if applicable) are shorter for DIP financed firms. The quick liquidation supports the monitoring role. DIP lenders do more than just selecting positive NPV projects. If the firm's situation worsens, they quickly liquidate to protect the assets value (Dahiya et al., 2003). Additionally, Flynn (1998) found that companies that receive DIP financing are more likely to successfully reorganize because liquidity is critical to maintain operations during the process and meet administrative costs.

Furthermore, Hotchkiss (1993) found that **larger firms**, measured by their assets pre-filing, are more likely to emerge as a going concern, than to liquidate. In many successful cases, the firms downsize throughout the reorganisation to generate operating capital. This explains, why larger firms have an advantage over smaller firms because they can divest more assets Hotchkiss (1993). Denise and Rodgers (2005) found results that support these findings. Their study showed that companies with a strong decline in **liabilities** and assets during the restructuring had a higher likelihood of emergence. Moreover, these cases also are more likely to be profitable after the bankruptcy (Denise & Rodger, 2005). Connected to this Atlman (2009) discovered that companies with excessive leverage after emerging have an increased chance of refiling.

Interestingly, LoPucki and Doherty (2015) identified a negative relationship between higher **pre-filing equity** and business survival and a positive relationship for highly levered firms. The authors explain this initially seemingly counterintuitive finding by differentiating between financial distress (excessive leverage) and economic distress (operating costs outweigh operating revenue). Bankruptcy works well in decreasing debt to reduce financial distress. However, it doesn't help much to when it comes to improving poor operating performance. Given firms with large equity accounts are mostly filing for Chapter 11 because they are facing economic distress, they don't benefit as much from the bankruptcy process and hence are more likely to fail. In support of this argument, LoPucki and Doherty (2015) also found that companies that enter bankruptcy with a positive operating income (EBIT) are more likely to survive.

Moreover, Ayotte and Morrison (2009) revealed that **asset liquidity and tangibility** of a firm strongly impacts the outcome of a Chapter 11 process. The authors argue that companies with high levels of tangible and liquid assets are more likely to receive secured debt. This in turn can increase the likelihood of a liquidation instead of a reorganisation as secured creditors may favour asset sales to recover their claims (Ayotte and Morrison, 2009).

Warren and Westbrook (2009) argue that **speed** is another factor that influences success. Most unsuccessful cases are pushed out early in the Chapter 11 process as "an efficient reorganization system should aim to dispose of the losers as soon as possible, avoiding both further delay and professional costs" (Warren and Westbrook, 2009). This was confirmed in their study. Successful cases, those that resulted in plan confirmation, took longer on average than cases that failed. The authors also analysed how firm **size** affects the success rate and attributed this in connection to speed. There are two contradicting views as to how firm size impacts speed. Firstly, the restructuring of larger firms might lead to greater challenges due the complexity of their operations and the need to negotiate with many creditors. However, larger companies have greater access to resources such as advisors and lawyers. The study found that on average the time it takes for plan confirmation is the same for small and large firms, but it the time it takes for large companies to fail is longer than for small companies (Warren and Westbrook, 2009).

Another interesting factor to consider when analysing the success of Chapter 11 filings is how **industry-wide distress** affects the outcome. Acharya et al.'s (2007) observed that firms filing for bankruptcies tend to emerge, rather than being sold or liquidated, when their industry is in distress. Those bankruptcy cases also have a higher duration on average. An industry is considered distressed if the median annual stock return is below or equal to -30% in the default year. The authors argue that this is due to a prevailing illiquidity in the market, which implies that there are few or no buyers for the distressed firm's assets (Acharya et al., 2007).

Harner and Marincic (2011) found that cases with a single **creditors' committee** were more likely to result in liquidation or a request for approval to sell substantially all assets than cases with no committee or multiple committees. Adlera et al. (2013) support these findings with their analyses on the shift from debtor to creditor control which became more prominent in the early 2000s as a result of the change in the UCC. Cases filed after 2001, have shown a trend towards liquidation rather than successful reorganization. Furthermore, those cases showed more frequent operating losses (Adlera et al., 2013). When looking at duration Harner and Marincic (2011) found that cases without a committee tend to overall conclude quicker but take longer to resolve motions to sell the majority of the debtors' assets. Creditors seem to value a quick resolution over a potential higher recovery through reorganisation (Harner and Marincic, 2011).

Distressed firms express a significantly **higher CEO turnover** which is the highest in the year of distress as well as the year after (Kang & Mitnik, 2014). Lin et al. (2020) found that CEO turnover significantly improves the likelihood of emergence after filing for Chapter 11. The authors argue that replacing the CEO signals credible commitment to the reorganization, increases managerial quality, particularly if the new CEO is a turnaround specialist, offers a new perspective and reduces management entrenchment.

LoPucki (2015) found that for cases which result in **363 Sales**, there is not only a decline in plan confirmation but also a lower business survival rate. In his paper with Doherty (2015) they go as far as saying that "a company that even hints in the press release announcing its bankruptcy that it intends to sell its business is highly likely to fail" to emerge. The authors argue that announcing to sell signals weakness to key stakeholders such as employees, customers and suppliers and to the market, which further weakens the company.

Furthermore, the level to which an informally settled plan before the filing has been established also impacts the outcome of a bankruptcy according to LoPucki and Doherty (2015). Companies that file with a **prepack or pre-negotiated** Chapter 11 are far more likely to survive.

While judges get randomly assigned to a bankruptcy case, management tries to influence the outcome and gain a strategic advantage through their choice of the bankruptcy court, which often is far from the headquarters (Chen, 2014). This is also known as **venue or forum shopping**. The phenomenon reflects an agency problem where managers act in the best interest of themselves or the shareholders, by choosing a debtor-friendly court, instead of maximizing the creditor's welfare. In the US most bankruptcy cases are filed in Delaware or the Southern District of New York. In general, Delaware is known to have more prepackaged cases and shows a greater deviation from the Absolute Priority Rule (APR; senior creditors must be paid in full before junior creditors or equity holders are paid), which indicates a wealth transfer between the creditors. New York tends to have longer durations and indicates lower recovery rates. Nevertheless, it still manages to attract large, complex and highly leveraged firms because of its procedural advantages and debtor-friendliness. This again illustrates the agency conflict in which the "creditors' welfare is likely to be exploited in the bankruptcy process" (Chen, 2014). Moreover, LoPucki and Doherty (2015) found that cases in Delaware and New York have a higher business survival rate. They argue that this is very likely the result of judicial experience in these courts, which also significantly increases the chances of survival. However, in 2002 LoPucki and Doherty identified a high refiling rate for companies that reorganized in Delaware or New York, which they explained by the court laissez-fair practices such as confirming plans quickly and with less scrutiny.

3. Data description

The study is drawn from a combination of publicly available bankruptcy filing data, firm-level financials and macroeconomic indicators to examine the factors that influence the outcome of a Chapter 11 reorganisation. The analysis integrates three primary data sources, which I loaded into Stata to conduct my statistical analysis:

First, I used the **Florida-UCLA LoPucki Bankruptcy Database (BRD)** as my main dataset which I then extended through other sources. The BRD is a comprehensive dataset that covers approximately 1,200 filings of large public US company bankruptcies between October 1979 and December 2022 (last updated in January 2023). To qualify as "large", a company must have reported at least $100 mn in assets (measured in 1980 USD – equivalent current dollars ≈ $310 mn) on its last 10-K prior to the bankruptcy filing. On top of that, the company must have submitted a 10-K or Form 10 with the U.S. Securities and Exchange Commission (SEC) for a fiscal year ending within three years prior to the bankruptcy. Both, Chapter 7 and Chapter 11 filings are included in the dataset. However, I dropped all Chapter 7 filings. Moreover, to guarantee a meaningful analysis all cases that were not clearly classified as either having emerged or failed to have emerged were dropped. Therefore, the last filing year I consider is 2021, because none of the observations in 2022 have been settled yet. This makes 2021 the end of my sample period. The observations are on firm-case level, meaning each row presents one bankruptcy case for a single firm. The data in a way is structured as cross-sectional with time-stamped variables. However, it is not true panel data but merely captures variables at different key events such as filing, confirmation and emergence date. With over 200 data fields on each filing, the BRD includes detailed information on key identifying variables (e.g., CUSIP, SIC code), filing specifications, legal and procedural characteristics, financial metrics, case outcomes, and industry variables.

Second, I created a dataset with annual financial data from **Compustat North America - Fundamental Annual** via the WRDS platform, to construct pre-filing and post-emergence firm-level variables. The extracted data included key identifying variables as well as key financials including total assets, cash, total debt, total liabilities EBIT, EBITDA and property, plant and equipment. I pulled this data for all U.S. firms in the BRD dataset with valid and standardised 9-digit CUSIP identifiers, which I constructed out of CUSIP6 and CUSIP9, available in the BRD dataset, beforehand. Furthermore, I downloaded another dataset from **Compustat North America - Fundamental Annual** to construct a measure of industry distress based on SIC codes. On top of the identifying variables, the dataset includes common shares outstanding, market value and fiscal-year-end stock price of the entire U.S. Compustat North America universe covering the period of the BRD dataset. I used this data to calculate year-over-year returns for each firm which I then used to construct the median annual return for each industry based on the SIC2 major group level.

The final data source I used is the **U.S. Bureau of Labor Statistics** from which I took the monthly Consumer Price Index for All Urban Consumers to calculate an average CPI for each year between 1980-2022. I used these values to adjust other financial variables to 2022 USD values to make them comparable.

After collecting all the data, I then merged it with the BRD dataset. As mentioned previously, the BRD dataset is not actual panel data but a somewhat incomplete combination between cross-sectional and time-series data. Therefore, I needed to merge the Compustat annual financial data twice with the BRD dataset with two different approaches to extract the data I needed. For the first step, I extracted firm-level financials from the Compustat dataset that reflect the company state right before filing. To do this I merged the data with BRD based on the filing date of the company's last 10-K report before filing for bankruptcy. I used a fuzzy merge on the CUSIP identifier I created and retained only those data points that are equal to or close to the 10-K filing date. I excluded all values that were reported more than 365 days prior the 10-K. In the cases in which multiple records matched my criteria, I included the one with the smallest time gap to the 10-K filing. In the second merge, I extracted financials at the time of emergence. When companies go through bankruptcy their identifiers such as the CUSIP sometimes change for example due to the issuance of new securities. Therefore, for the variables measured at emergence, it might be misleading to match based on the CUSIP at filling. The BRD also provided the gvkey, a unique company identifier assigned by Compustat, at filing and at emergence. Hence, I use the gvkey to robustly match the Compustat emergence financials to the BRD dataset based on the year of emergence.

Then I merged the dataset which contains the Compustat median industry returns which I calculated earlier. I matched them based on the firms' 2-digit SIC codes and the fiscal year of the last available financial record prior to filing. Additionally, to ensure comparability of values across time I matched the CIP dataset to both the year of the last 10-K filed and the year of emergence. This allowed me to adjust key financial variables for inflation by expressing them in 2022 dollars.

My final dataset combines cross-sectional and firm-level data for around 900 bankruptcy cases filed between 1980 and 2021. At its core, it consists of Chapter 11 case characteristics from the BRD, which are then extended by more detailed firm level financial data and industry-level distress measures from Compustat and adjusted for inflation using the U.S. Bureau of Labor Statistics CPI.

Despite the scope and depth, the dataset does face certain limitations that should be kept in mind. First, some observations suffer from missing or incomplete data. Moreover, in some cases the Compustat data could not be matched due to outdated or missing CUSIP identifiers. Regarding the inflation adjustments through CPI, the simplification of assuming uniform inflation across sectors may not reflect firm-or industry specific changes. Finally, the BRD coverage is comprehensive but more representative post-2000 due to better data availability.

4. Methodology

4.1. Defining success – dependent variables

As mentioned in the literature review, there are many different approaches to measure if a reorganization process under Chapter 11 has been successful. I decided to look at the question from three different angles to capture both procedural and operational outcomes: the likelihood of emergence from Chapter 11, the likelihood of refiling again and changes in the operating performance during the reorganization process. However, the data availability for the variable measuring operating performance is very low. Therefore, the quality of the results might suffer, which is why the focus of this study relies on the first two dependent variables.

4.1.1. Emerged from Chapter 11

The first dependent variable, '**Emerged From Chapter 11',** is a binary indicator which assess the procedural outcome of a reorganisation. It reflects the widely accepted view in the literature that the main goal of a Chapter 11 process is to avoid liquidation and instead restructure a business in such a way that it continuous to operate indefinitely as an independent entity. This definition goes beyond viewing simple plan confirmation as a measure of success. Instead, it aligns with Altman's (2009) view and LoPucki's business survival variable.

To be considered emerged (binary indicator equals one) the company must continue to exist independently, which can be either through a reorganisation confirmation or under a 363 sale. If a company gets liquidated or continues to operate only for the purpose of being liquidated in the future it does not classify as emerged (binary indicator equals zero). Finally, if a company is acquired it is still considered to be emerged as long as it continues to operate as a separate business. Cases in which it was not possible to determine if the company emerges (e.g., due to early dismissal) are not classified and excluded in the variable.

4.1.2. No refiling within 5 years

My second dependent variable, '**No Refiling Within 5 Years',** indicates whether a firm refiled for bankruptcy within 5 years of its emergence. It is also a binary indicator and equal to one if no refiling occurred and zero otherwise. Using refiling as a measure of reorganisation success is another well-accepted approach among researchers. I only considered refiles in which more than half the company's operations are included as actual refiles. This approach ensures an analysis of systematic success or failure at firm-level. It also reduces ambiguity and enhances transparency and reproducibility as partial re-filings were not always clearly documented. Moreover, I decided to use a five year cut off value to be in line with LoPucki's (2015) study that found that most re-filings that occur 5 years after the initial Chapter 11 process are due to reasons thar are unrelated to the first filings.

4.1.3. EBITDA sign change (operational success)

Finally, to capture improvements in operating performance I constructed the variable '**EBITDA Sign Change'**. I based the measure on EBITDA to provide a cash based view of core profitability. By excluding depreciation and amortization the effect of non-cash accounting charges related to past capital investments - which vary significantly by industry and accounting policy – is isolated. This makes EBITDA a more comparable indicator of changes in operational performance across companies. 'EBITDA Sign Change' is another binary indicator, equal to one if EBITDA has moved from negative in the last 10-K before the filing to positive in the first 10-K after the emergence, and zero otherwise. The variable indicates whether the company was able to achieve a successful turnaround of operations. It is important to note that this approach does not consider practical improvements if the EBITDA stays negative and cases in which the EBITDA was positive at the time of the last 10-K before filing. It isolates firms that truly achieved an operational turnaround.

In this study I decided to exclusively focus on these four success measures as I believe they best capture successful outcomes of a corporate reorganisation under Chapter 11. Alternative dependent variables proposed by prior literature, such as plan confirmation, duration or CEO turnover, in my opinion are either incomplete, meaning they are missing steps to actually indicate true success or are better conceptualised as independent variables. A confirmed reorganization plan for example is essential to be able to officially reorganize. Nevertheless, a plan confirmation still leaves a lot of ambiguity in terms of execution of that plan and the final and desired outcome is to emerge. Moreover, changes in management are a response to distress and an attempt to turn the operations around. However, it does not reflect if a recovery was achieved.

4.2. Independent variables

	Variable	**Description**
Financial characteristics	Cash Ratio	The **Cash Ratio** is defined as the natural logarithm of the CPI-adjusted cash and cash equivalents divided by total assets. To capture different points in time depending on the success measure, the variable is split into two versions: - **Pre-Filing Cash Ratio** – reflects liquidity at the time of the last 10-K before filing - **Emergence Cash Ratio** - reflects liquidity in the year of emerging

		Both the pre- and post-emergence cash ratios are highly skewed to the right. Therefore, the natural logarithm of the cash ratio is used in the regression analysis to reduce the impact of extreme values. Main data source(s): WRDS (Compustat) & BRD
	Leverage	**Leverage** is measured as the natural logarithm of the CPI-adjusted total liabilities to total assets. To capture different points in time depending on the success measure, the variable is split into two versions: - **Pre-Filing Leverage**– reflects the capital structure at the time of the last 10-K before filing - **Emergence Leverage** – reflects the capital structure in the year of emerging Due to a highly right-skewed distribution of leverage in both periods, the natural logarithm of leverage is used in the regression analysis to reduce the impact of extreme values. Main data source(s): BRD
	ROA	The **ROA** variable is expressed as the CPI-adjusted ratio of EBITDA to book assets. To capture different points in time depending on the success measure, the variable is split into two versions: - **Pre-Filing ROA**– reflects the operating profitability at the time of the last 10-K before filing - **Emergence ROA** – reflects operating profitability in the year of emerging Although the data is highly skewed, it is heavily skewed to the left due to extremely negative outliers. Therefore, a log-transformation cannot be applied, and the raw values are used. However, to ensure that these values don't distort the results, a winsorization is applied in the robustness section. Main data source(s): BRD
	Firm Size	The **Firm Size** is measured as the natural logarithm of the CPI-adjusted total assets. To capture different points in time depending on the success measure, the variable is split into two versions: - **Pre-Filing Firm Size** – reflects the scale of the business at the time of the last 10-K before filing - **Emergence Firm Size** – reflects the scale of the business in the year of emerging Even though only the total assets of the pre-filing period are heavily rightly skewed, the natural logarithm was used for both periods to ensure consistency. This reduces the impact of extreme values and aligns with standard practices in bankruptcy research. Main data source(s): BRD

	Tangibility	Tangibility is defined as the CPI-adjusted ratio of property, plant and equipment to total assets. To capture different points in time depending on the success measure, the variable is split into two versions: - **Pre-Filing Tangibility** – reflects the asset composition at the time of the last 10-K before filing - **Emergence Tangibility** – reflects the asset composition in the year of emerging The time period at emergence indicates slightly elevated skewness. However, because the skewness is only moderate and because zero values are present in the data no log transformation is applied. Main data source(s): WRDS (Compustat) & BRD
Industry condition	Industry Distress	**Industry Distress** is a binary indicator that equals one if the firm's 2-digit SIC industry indicates a median annual return of -30% or less, and zero otherwise. Firm level annual returns are calculated as the current share price minus the lagged price, divided by the lagged price per firm. Those values were then aggregated based on the SIC2 industry code. Similarly to the variables capturing financial characteristic, this dummy was created for two points in time, creating: (1) **Pre-Filing Industry Distress** (2) **Emergence Industry Distress**. These variables assess if there was an industry wide financial pressure to capture the impact of economic conditions just before filing and at emergence. Main data source(s): WRDS (Compustat) & BRD
Bankruptcy process characteristics	DIP Financing	**DIP Financing** is a binary indicator that equals one if the firm received a DIP loan throughout the Chapter 11 process. Main data source(s): BRD
	Duration	**Duration** is expressed as the natural logarithm of the time between filing date and confirmation date in days. Duration is highly skewed to the right with a few very long cases. Therefore, a log transformation is applied to reduce the impact of these outliers. Main data source(s): BRD
	Free-Fall Filing	**Free-Fall** is a binary indicator that takes a value of one if a company filed for Chapter 11 without a pre-negotiated or prepackaged plan, and zero otherwise. A case is considered prepackaged if the debtor obtained the necessary votes by the impaired creditors for a reorganization plan prior to filing for bankruptcy. If the debtor negotiates a reorganization plan with at least one major creditor and gets their support the case is considered pre-negotiated. While the free-fall variable is used in the main regression, for further specification two additional indicators were created:

<table>
<tr><td></td><td></td><td>

Prepack (equals one if company enters with prepacked plan, and zero otherwise)
Pre-Negotiated (equals one if company enters with pre-negotiated plan, and zero otherwise)

Main data source(s): BRD
</td></tr>
<tr><td></td><td>Sale Under Chapter 11</td><td>
Firm Sale is a binary indicator that is equal to one if a major sale either through Section 363 or as part of a confirmed plan occurred, and zero otherwise.
While the firm sale variable is used in the main regression, for further specification two additional indicators were created:

363 Sale (equals one if debtor sells all or most of its assets under section 363, and zero otherwise)
Sale Intended (equals one if the debtor intended to sell all or most of its assets before filing for bankruptcy, and zero otherwise)

Main data source(s): BRD
</td></tr>
<tr><td>Governance / legal features</td><td>CEO Replaced</td><td>
CEO Replaced is a binary indicator that equals one if the CEO in place at the filing date was replaced throughout the Chapter 11 process, and zero otherwise.
Main data source(s): BRD
</td></tr>
<tr><td></td><td>Committees</td><td>
Creditors' Committee is a binary indicator that equals one if an official committee representing unsecured creditors, was appointed, and zero otherwise.
While the creditors' committee variable is used in the main regression, for further specification two additional indicators were created:

Equity Committee (equals one if an official committee representing equity holders, was appointed, and zero otherwise)
Retiree Committee (equals one if an official committee representing retirees, was appointed, and zero otherwise)

Main data source(s): BRD
</td></tr>
<tr><td></td><td>Delaware Or New York</td><td>
Delaware Or New York is a binary indicator that equals one if the case was filed either in New York City or in Wilmington, Delaware, and zero otherwise. This variable captures the potential impact of filing in the two most prominent bankruptcy courts.
While the Delaware Or New York variable is used in the main regression, for further specification two additional indicators were created:

Delaware (equals one if the case was filed in Wilmington, Delaware, and zero otherwise)

</td></tr>
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		- **New York** (equals one if the case was filed in New York City, and zero otherwise) Main data source(s): BRD

5. Descriptive statistic

Figure 1. *Chapter 11 filings per year*

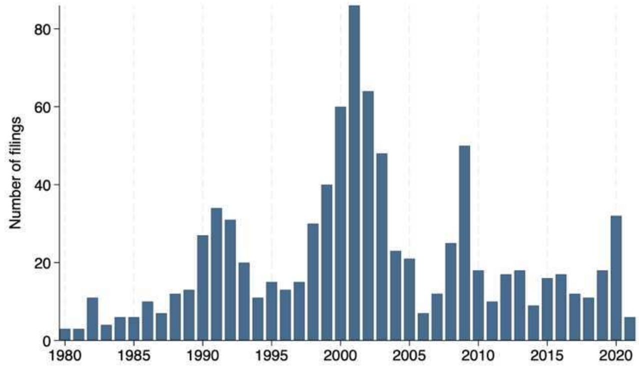


Figure 2. *Evolution of the total number of listed U.S. companies per year (1980-2022)*

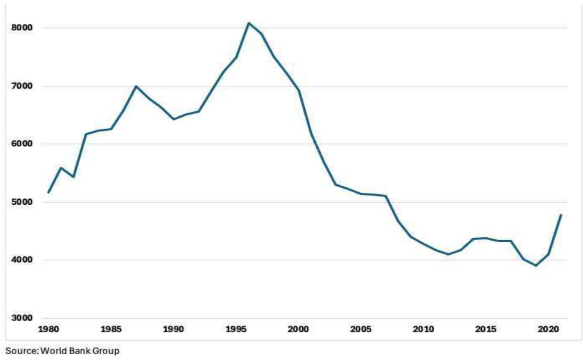


Figure 1 plots the number of Chapter 11 filings per year from 1980 till 2021. The graph is very much in line with the trends one would expect. First of all, it is important to keep in mind that these are not all U.S. Chapter 11 filings that occurred during the time frame but just the ones of public companies that fit the requirement of the BRD dataset. When comparing the overall shape of the graph to the number of public U.S. companies over the same time period in Figure 2, the evolution is very well reflected in the number of case filings, which makes sense. If the number of public companies rises, the average rate of public bankruptcies must increase and vice versa.

Furthermore, recession and regulation driven spikes/dips can be observed in Figure 1. There is a sharp rise in bankruptcies visible between the mid-1990s, which could be due to the early 1990s recession. The number of bankruptcy filings peaks in the early 2000s, with the highest number of observations in 2001, which directly overlaps with the Dot-Com Recession. Another big surge appears in 2008/2009 which is in line with the Great Recession. In 2006 the number of case filings drops quite heavily. This is likely due to the adoption of the BAPCPA in 2005, which made filing for Chapter 11 less attractive. The sharp increase in 2020 is very likely to be related to the economic downturn causey by Covid-19 lockdowns.

5.1. Dependent variables

Table 1. *Summary statistics – dependent variables*

Variable	Mean	SD	Min	Max	N
Emerged From Chapter 11	0.648	0.478	0	1	879
No Refiling Within 5 Years	0.850	0.357	0	1	568
EBITDA Sign Change	0.335	0.473	0	1	260

Figure 3. *Number of non-missing observations by filing year*

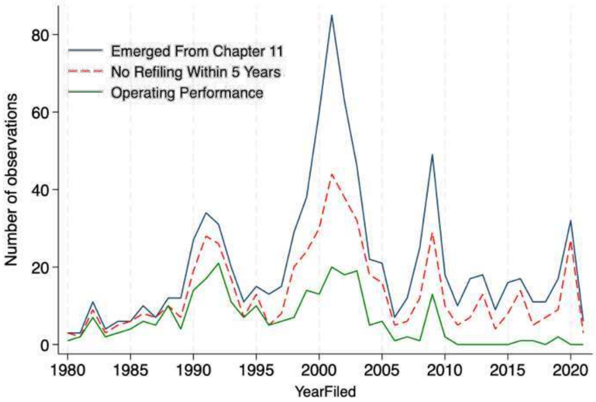
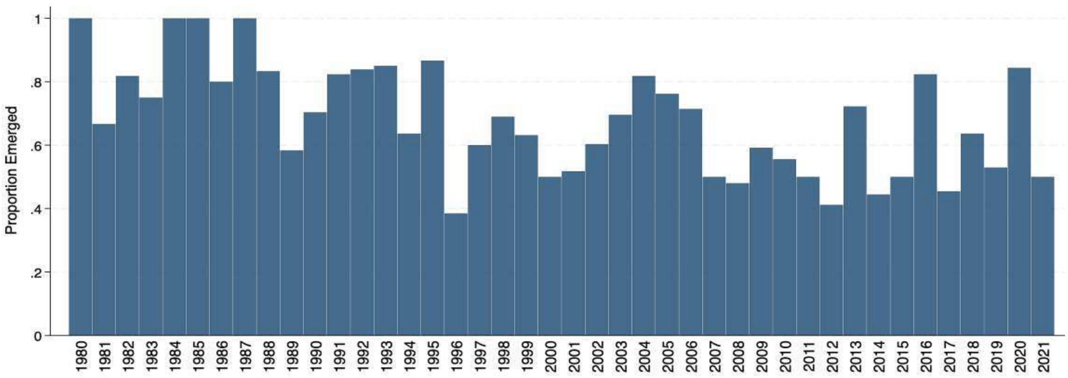


Table 1 reports the cross-sectional averages of my dependent variables. Generally, it can be said that on average around 65% of the companies that filed for bankruptcy were able to emerge from Chapter 11. Of those companies that emerged only around 25% refiled again within a five-year period. Moreover, 33.5% of the companies that emerged experienced a change from a negative EBITDA at the point of filing to a positive EBITDA at emergence. When looking at the number of observations (Figure 3) it is important to keep the significantly smaller sample size, particularly for operating performance, in mind. It is intuitive that the number of observations for the refiling and EBITDA variables must be significantly smaller than for the emergence variable because having emerged is a prerequisite for a case to be considered in the other two success measures. Nevertheless, especially the number of observations for the operating performance in the second half of the sample period is extremely low due to data availability issues and might not represent the actual population. As stated earlier, this is why the regression analysis will focus on the emergence and refiling measure.

Figure 4. *Emergence success rate by filing year*



In the early and 1980s **emergence rates** have been very high, even reaching 100% in some years (Figure 4). Starting from the late 1980s a decline in the average case emergence is visible with rates of around 75% in 1988 to 1995. Success rates then plunged to roughly 55% until they increased again 2002. This decrease in emergence success coincides with the Bankruptcy Reform Act which increased the plan confirmation standards. The strong increase in emergence rate in the early 2000s reflects the overall shift in the Chapter 11 environment at that time that started to become more confident with features such as prepacks, DIP financing and RSAs. Since 2007, emergence rates have tumbled to between 50-60% with a few exceptional strong years.

Figure 5. *5 years refiling rate by emergence year*

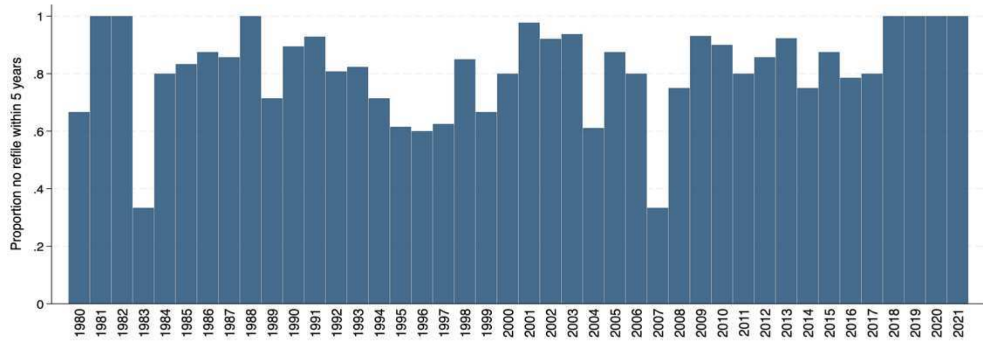


Figure 6. *Proportion of cases which indicated a positive sign change in their EBITDA from filing to emergence*

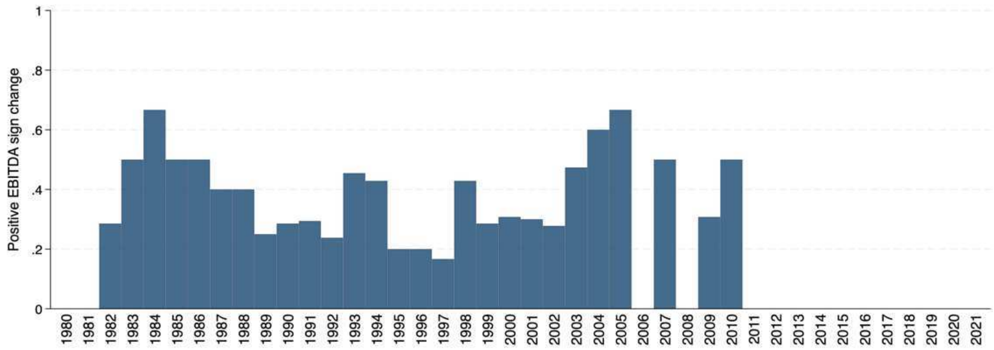
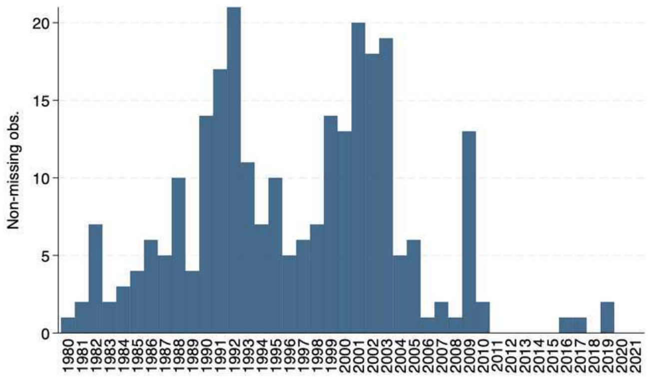


Figure 5 shows the percentage of companies that did <u>not</u> refile <u>within five years of emergence</u> based on their emergence year. Therefore, the years 2018 – 2021 should be disregarded, because some of the companies might have refiled for bankruptcy after the observation period ended. Hence, the 100% success rates in these years are misleading. The refiling rates appear to be more stable than the emergence rates, except for the emergence years 1983 and 2007. In these two years re-filing rates spiked with almost 70% of the emerged companies refiling within 5 years. The first spike directly precedes the 1984 Amendments' which tightened exclusivity rules. The second dip is likely the result of a rapid resurgence of financial distress after emergence as the global credit market collapsed as part of the financial crisis.

Figure 7. Count of non–missing EBITDA improvement observations by filing year



As mentioned earlier, the number of observations for the operational performance measure if extremely low, especially in the beginning and ending of the sampling period with a few years even having zero observations (Figure 7). Therefore, assumptions on specific trends on a year-by-year basis might be flawed. In the regression, analysis of the years after 2010 will be disregarded entirely and the sample will be divided into only two time periods (the other two success measures will be divided into more), to ensure that each period has enough observations for a meaningful result.

5.2. Independent variables

Table 2. *Summary statistics – independent variables*

Variable	Mean	SD	Min	Max	N
Pre-Filing Cash Ratio (log)	-3.709	2.853	-24.087	-0.145	876
Emergence Cash Ratio (log)	-2.860	1.684	-16.512	-0.026	249
Pre-Filing Leverage (log)	-0.085	0.405	-2.793	2.024	879
Emergence Leverage (log)	-0.251	0.605	-6.181	1.634	250
Pre-Filing ROA	-0.048	0.222	-3.391	0.378	865
Emergence ROA	0.070	0.117	-0.928	0.407	259
Pre-Filing Firm Size (log)	7.240	1.142	5.714	13.751	879
Emergence Firm Size (log)	6.897	1.396	2.419	12.133	283
Pre-Filing Tangibility	0.376	0.282	0	2.131	856
Emergence Tangibility	0.365	0.271	0	2.063	244
Pre-Filing Industry Distress	0.187	0.390	0	1	879
Emergence Industry Distres	0.063	0.242	0	1	879
DIP Financing	0.543	0.498	0	1	879
Duration (log)	5.792	1.037	1.386	8.499	819
Free-Fall	0.711	0.454	0	1	879
Firm Sale	0.484	0.500	0	1	829
CEO Replaced	0.620	0.486	0	1	861
Creditors' Committee	0.844	0.363	0	1	864
Delaware Or New York	0.519	0.500	0	1	879

Table 2 displays the summary statistics of the dependent variables. I always included the values of the pre-filing and emergence variables to better understand how they change during the process of bankruptcy. As with the operational performance variable the data coverage for the financial variables at emergence is extremely low and therefore should always be analysed critically.

Starting with the **financial characteristics** and **industry conditions**, the cash ratio, expressed in logs, has a mean of -3.709, increasing to 2.853 at emergence, which indicates that firms tend to increase their cash holdings relative to assets during a Chapter 11 process. The leverage ratio also, also expressed in logs, has a pre-filing mean of -0.085 which slightly declines to -0.251 at emergence. Hence, a moderate decrease in leverage is visible. The mean ROA is negative in the pre-filing period (-0.048) and as one would expect, improves throughout the process, reaching a positive 0.070 at emergence. The firm size variable also indicates considerable dispersion and decreases slightly from the pre-filing period (mean log-assets 7.240 ≈ $1,392mn in total assets) to the time of emergence (mean log-assets 6.897 ≈ $987mn in total assets). The proportion of tangible assets remains relatively stable when comparing the pre-filing mean of 0.374 to the emergence mean of 0.365. Additionally, the proportion of industry distress is notably higher pre-filing (0.187) then at emergence (0.063). This seems consistent with firm being forced to enter bankruptcy due to a sector-wide downturn which may have eased by the time they emerge. Figures 8 - 12 further underline these observations.

***Figure 8.** Average pre-filing vs. emergence cash ratio by filing year - no log*

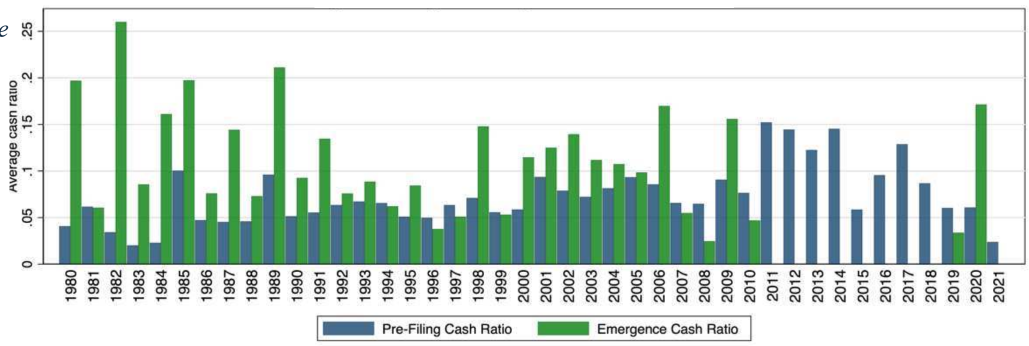


***Figure 9.** Average pre-filing vs. emergence leverage ratio by filing year - no log*

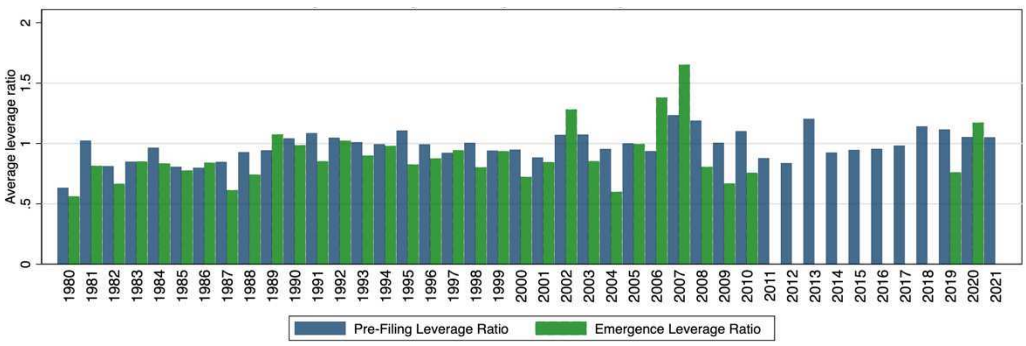


Figure 10. Average pre-filing vs. emergence firm ROA by filing year - no log

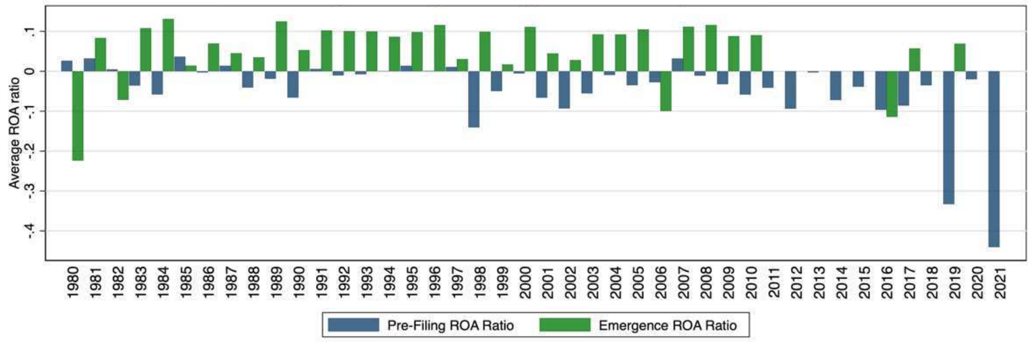


Figure 11. Average pre-filing vs. emergence size by filing year

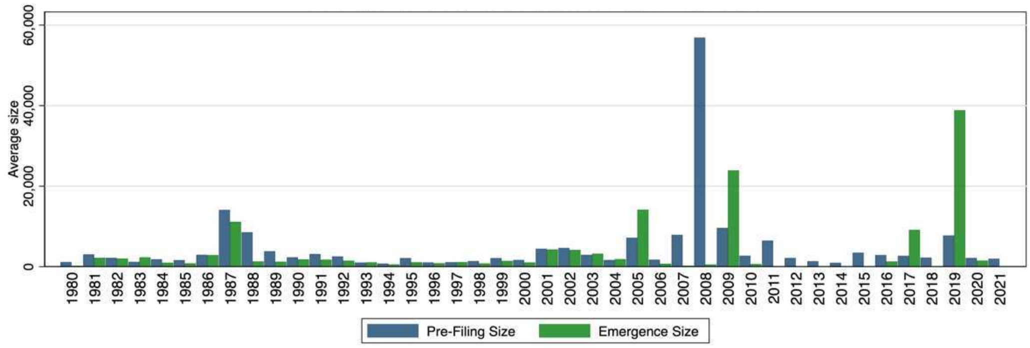


Figure 12. Average pre-filing vs. emergence tangibility by filing year

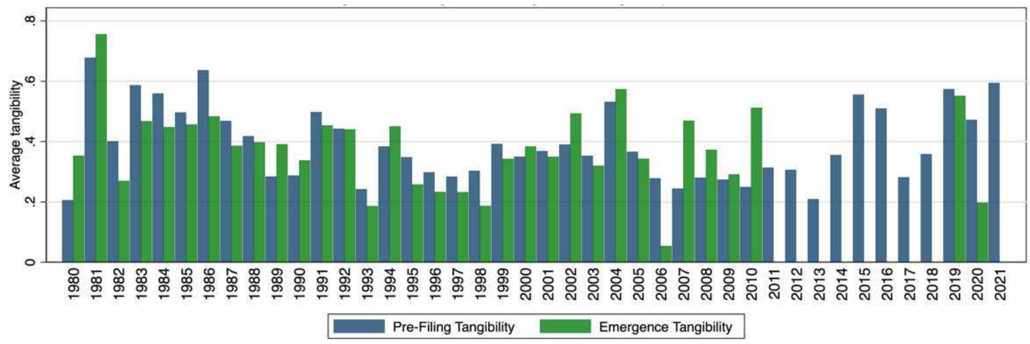


Figure 8 shows the development of the average cash ratio as a raw value based on the filing year. The plot confirms that the cash ratio at emergence is on average much higher, than at filing. Moreover, in particular the pre-filing observations indicates a positive skew, highlighting the importance of using the natural logarithm. In contrast, the values at emergence seem to be more evenly distributed. However, between 2011 and 2018 there is almost no available data for total assets at emergence in neither the BRD nor the Compustat dataset. As total assets are part of all of the financial measures the same gap is visible in all other figures.

Figure 9 confirms that on average the leverage ratio decreases slightly during the Chapter 11 process. While the graph suggests a rather even distribution, further analysis indicated that due to a few extreme outliers, leverage is heavily skewed (5.28) and heavily tailed with a kurtosis of 56.66. Therefore, a log transformation is essential to improve the interpretability of the regression analysis. The yearly ROA averages in Figure 10 clearly support the earlier findings that, with a few exceptions, companies are able to turn their negative ROA pre-filing into positive values throughout the reorganisation. Figure 11 illustrates the slight decrease in firm size from the pre-filing period to emergence and strongly indicates that the data is skewed, confirming the decision to apply a log transformation. Regarding the asset tangibility in Figure 12, the values pre-filing and at emergence are rather close when compared to the other graphs, which is also implied by the close means of the two variables.

Figure 13. *Average pre-filing vs. emergence industry disstress rate by filing year*

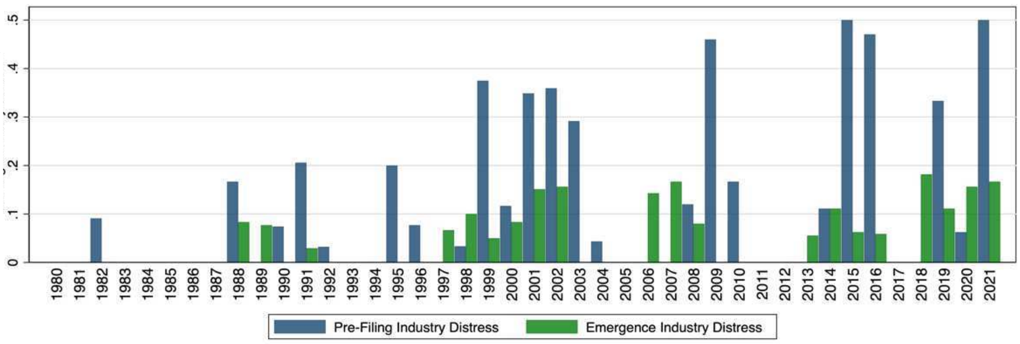
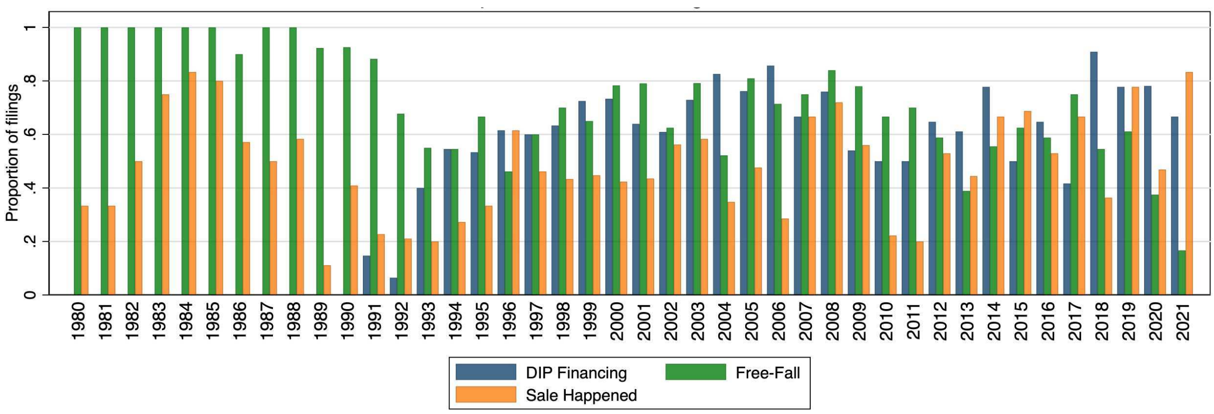


Figure 13 plots the average industry distress rate per filing year. In this chart years with a rate of zero do not indicate a lack of observations but imply, that none of the SIC2 industries had an average return of -30% or less. The spikes in the graph are in line with broader economic downturns. Moreover, pre-filing industry distress levels are consistently higher than at emergence, which suggests that firms often emerge in more favourable conditions.

Figure 14. *Proportion of DIP financing, free-fall and firm sale cases by filing year*



Regarding the **bankruptcy process characteristics,** it can be said that with a mean of 0.543 a bit over half of the companies in the sample used DIP financing as part of their reorganisation. The first observations of cases which used DIP financing were in 1991. Since then, the use has steadily increased and is at around 60% since 2010 (Figure 14), which is consistent with prior literature. Moreover, over 70% (mean = 0.711) of all observations across the entire sample period were free-fall cases. Figure 14 shows that before the early 1990s almost all cases were free-fall. Since then, the use of prepacks and pre-negotiated plans has significantly increased. With a mean of 0.484, on average 48% of the cases included a firm sale either through section 363 or as part of a confirmed plan during the entire sample period. While in the 1980s these sales have been quite popular, there is slight decrease in the variable afterwards. However, in recent years the percentage of cases that includes an asset sale has increased again. This could be explained the increased use of section 363 found in prior literature.

Figure 16. *Average Chapter 11 case duration by filing year (no log)*

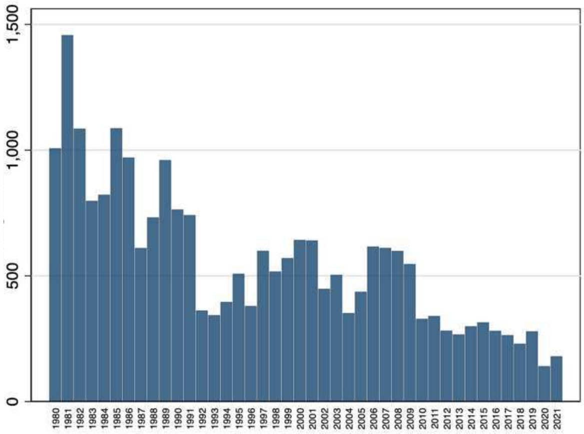
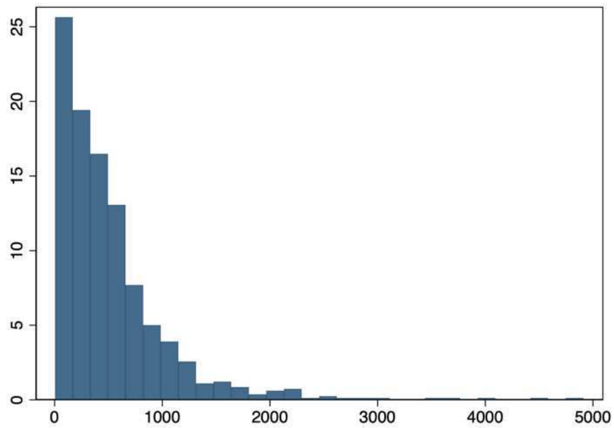


Figure 15. *Chapter 11 case duration distribution (no log)*



As shown in Figure 16, there has been a significant decline in duration over time, which is in line with what other scholars found. In the early 1980s cases took on average more than one thousand days, while by the 2000s and especially post-2010, the average durations have fallen well below five hundred days. This likely reflect the greater use of pre-packaged and pre-negotiated bankruptcies as well as DIP financing seen in Figure 14. Figure 15 shows that the variable duration is heavily skewed to the right with a few extreme high duration outliers, which justifies the log transformation. The mean log duration is 5.79 (≈ 327 days) which implies that the typical case lasts just under a year.

__Figure 17.__ Proportion of cases with CEO replacement, creditor's committe and filing court in Delaware or New York by filing year

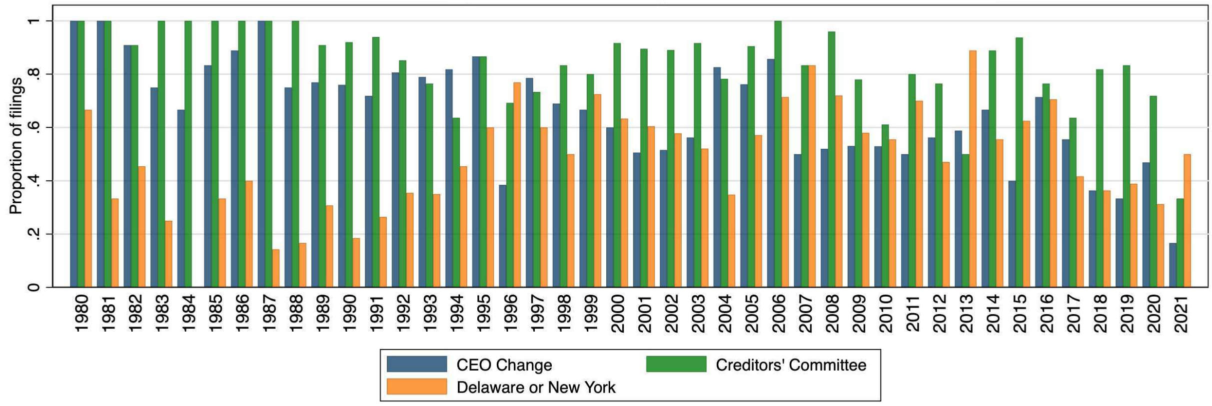


Figure 17 summarizes the evolution of three key governance and legal characteristic across Chapter 11 cases. With a mean of 0.620, CEO turnover occurred in around 62% of the cases on the sample and creditors' committees were formed in 84% (mean = 0.844). CEO turnover and the use of creditors' committee stays relatively consistent, in particular in the first half of the sample period and then slightly declines in the second half. Furthermore, the summary statistics show that slightly over half of the cases were filled in Delaware or New York (mean = 0.519). The Delaware/New York filing rate appears to have increased starting in the mid 1990s and remains well above 50% in most years. These high filing rates indicates that companies engage in venue shopping to receive more favourable treatment during the Chapter 11 process.

6. Case examples

6.1. Lehman Brothers Holding Inc – no emergence

Lehman Brothers filed for bankruptcy on 15.09.2008. With over 200 subsidiaries in over 20 countries, $1.2 bn in creditor claims and more than 900,000 derivative contracts in place, this date marks the beginning of one of the largest and most complex bankruptcies in the U.S. history (Fleming & Sarkar, 2014). Furthermore, the case is a prime example for how poor preparation for a potential bankruptcy can cause further inflammation to the situation. Serious consideration of bankruptcy by the company's management came just a few days before filing. The company delayed hiring legal counsel and developing a strategy until the very last minute. On top of that, management failed for file standard first-day motions which are needed to, for example, authorize continued operation and maintain cash management systems. This last-minute approach led to further disruptions in operations, significant financial losses, estimated at $75 bn and numerous creditor disputes (Fleming & Sarkar, 2014).

In the end, Lehman Brothers did not emerge from bankruptcy but liquidated under Chapter 11 through selling its assets. As part of that liquidation Lehman Brothers sold its broker-deal unit to Barclays as a 363 sale. Lehman Brothers Chapter 11 plan was finally, confirmed on 06.12.2011 (Fleming & Sarkar, 2014), implying a duration of 1,177 days.

Given Lehman Brothers was not able to emerge from Chapter 11 the case can be considered unsuccessful. Additional inputs from dataset:

Pre-Filing Cash Ratio:	0.275
Pre-Filing Leverage Ratio:	0.967
Pre-Filing ROA:	0.069
Pre-Filing Firm Size:	$937.41 bn
Pre-Filing Tangibility:	0.01
DIP Financing:	Yes
Free-Fall:	Yes

CEO Replaced:	Yes
Creditors' Committee:	Yes
Equity Committee:	No
Retiree Committee:	No
New York:	Yes

6.2. General Motors (GM) – successful emergence

The economic downturn 2008 hit the automotive industry quite hard. On top of that General Motors had suffered from a long-lasting decline in performance (Nygaard, 2022). The U.S. government classified GM as too important for the U.S. economy to fail and provided a $13.4 bn bridge loan to the company. Moreover, the Obama administration, which took over in 2009, formed and Auto Task Force to oversee the restructuring of GM. The company filed for Chapter 11 on 06.01.2009 and used section 363 to quickly sell its most viable assets to a newly created entity. The operational restructuring was mainly driven by a reduction in work force, health benefits, production plants and product lines. Furthermore, to support operations during the reorganisation GM received a DIP financing loan of $30.1 bn by the Treasury. GM emerged from Chapter 11, just 40 days after filing, on 10.07.2009. In 2013, the US government exited their investment and realized a loss of around $10.5 bn (Nygaard, 2022).

The General Motors Chapter 11 filing was successful on both the emergence and no refiling level. However, the company was not able to turn its negative EBITDA at the point of filing into a positive one at emergence. As is highlighted in the above analysis, General Motors received material support from the US Government during the Chapter 11. It could be argued that without this support and realised loss on the Government's behalf, the outcome may have been less positive given the macroeconomic factors for the sector. Additional inputs from dataset:

Pre-Filing Cash Ratio:	0.15
Emergence Cash Ratio:	0.27
Pre-Filing Leverage	1.94
Emergence Leverage :	0.79
Pre-Filing ROA:	-0.13
Emergence ROA:	-0.03
Pre-Filing Firm Size:	$125.28 bn
Emergence Firm Size:	$185.92 bn
Pre-Filing Tangibility:	0.45
Emergence Tangibility:	0.14

Pre-Filing Industry Distress:	Yes
Emergence Industry Distress:	No
CEO Replaced:	Yes
Creditors' Committee:	Yes
Equity Committee:	No
New York:	Yes

6.3. Mattress Firms Holding Corp – prepackaged

The Mattress Firms case is an example of how a prepackaged bankruptcy can lead to a quick and successful reorganisation (BedTimes, 2018). The company filed for Chapter 11 on 05.11.2028 in Delaware. Mattress Firms had a prepackaged plan in place that enabled new financing and allowed the company to initially close up to 700 underperforming stores, while continuing to fully operate and to pay suppliers as well as contractors. Mattress Firms emerged just 48 days later on 11.11.2018 with an optimized balance sheet supported by $525 mn in exit financing and a streamlined store footprint following the closure of approximately 900 locations (BedTimes, 2018).

To summarize the success of Mattress Firms reorganisation under Chapter 11, it can be said that the case was successful on the emergence and no refiling level. The EBITDA success measure is not relevant for this specific case, as the company entered bankruptcy with a positive EBITDA. Additional inputs from dataset:

Pre-Filing Cash Ratio:	0.001
Pre-Filing Leverage:	0.693
Pre-Filing ROA:	0.104

DIP Financing:	Yes
Firm Sale:	No
CEO Replaced:	Yes

Pre-Filing Firm Size:	$1.955 bn		**Creditors' Committee:**	No
Pre-Filing Tangibility:	0.198		**Equity Committee:**	No
Pre-Filing Industry Distress:	No		**Retiree Committee:**	No
Emergence Industry Distress:	No		**Delaware:**	Yes

6.4. Phoenix Steel – refiling

Phoenix Steel, was a small steel producer, operating in Delaware and Pennsylvania (Whitford, 1994). The company filed for Chapter 11 on 08.12.1983. Its largest shareholder at the time, a French steel company, was also in insolvency. The company renounced its pension obligation, leaving the federal pension insurer as the largest unsecured creditor, while the French parent waved all claims. This meant that the board was no longer accountable to its parents and operated independently. The management prioritised keeping the mills running by cutting wages and was looking for potential buyers and investors. After initial difficulties, Phoenix Steel secured financing by an investor group, which took full ownership of the company. This allowed the company to receive confirmation of their reorganisation plan on 31.08.1985. However, just two years later, the company refiled for bankruptcy. During this process, both mills were sold off to two separate companies which kept operating them, but leaving creditors from first reorganization with almost no recovery. The case illustrates how Chapter 11 can preserve jobs and operations, with the risk of potential losses to creditors in the long run (Whitford, 1994).

Mattress Firms reorganisation under Chapter 11 was successful on the emergence level, but failed when measuring success based on avoiding refiling within 5 years of emergence. Moreover, no EBITDA at emergence is available for this case. Additional inputs from dataset:

Pre-Filing Cash Ratio:	0.002		**DIP Financing:**	No
Pre-Filing Leverage:	0.91		**Free-Fall:**	Yes
Pre-Filing ROA:	-0.04		**Firm Sale:**	Yes
Pre-Filing Firm Size:	$406 mn		**CEO Replaced:**	Yes
Pre-Filing Tangibility:	0.61		**Creditors' Committee:**	Yes
Pre-Filing Industry Distress:	No		**Equity Committee:**	No
Emergence Industry Distress:	No		**Delaware:**	Delaware

7. Regression analysis - output

As described in the methodology section I constructed three dependent variables measuring the emergence success, if the emerged company refiled within 5 years and if the company was able to turn its negative EBITDA positive. I then performed a series of logistic regressions for each of the dependent variables. More specifically, I developed 4 – 7 regression models for each dependent variable in which I first assessed the impact of my 13 main independent variables, which I then extended to my more specific sub-independent variables based on data availability. To ensure that multicollinearity is not a concern, I used the "pwcorr" command in Stata to test for pairwise correlations. Furthermore, all models were estimated using the "robust" command in Stata to obtain heteroskedasticity-consistent standard errors and ensure valid statistical inference across firms with varying characteristics and financial conditions. Model (1) always takes into consideration the entire sample period (1980-2021) without industry fixed effect. Model (2) also takes the entire sample period, but industry fixed effects are added. All following models also account for industry fixed effects. Model (3) and (4) divide the sample into two equal periods from 1980-2000 and 2001-2021. All following models are slightly adjusted based on the data availability of each success measure in will be explained in the respective section.

7.1. Emergence success

The goal of my first regression analysis is to identify factors that influence the likelihood of companies to emerge from Chapter 11, measured by dependent binary variable 'Emerge Success'. The analysis includes a series of regression models with models (1) – (4) following the standard structure described above. To gain a more nuanced understanding of how the influence of the independent factors has changed over time, I initially intended to split both periods into sub-samples. However, due to a small sample size in the earlier years, I decided it makes sense to only divide the second period (2001-2021) into two sub-periods: 2001 – 2010 (5) and 2011-2021 (6). Moreover, in model (7) I replaced the variable 'Free-Fall' by 'Prepack' and 'Pre-negotiated', the variable 'Firm Sale' by 'Sale 363' and 'Sale Intended' and the variable 'Delaware or New York' by 'Delaware' and 'New York', to analyse if further specifications make a difference. I also added the equity and retiree committee variable. I initially did this for both time period, 1980-2000 and 2001-2021. However, because many of the sub-categories have not been well established in the first period, e.g., until 1990 there was one prepack case, I only applied this specification to the second time frame (2001-2021). Overall, the pseudo R2 indicates a good fit of the model, with slightly higher values for models (5) – (7).

Starting with the financial variables, the **cash ratio** at filing with the expectation of model (3) all coefficients are slightly negative. However, given that only model (6) indicates a significant p-value and also only a 10% level, the cash ratio overall does not seem to be a strong predictor for emergence success. The pre-filing **leverage ratio** indicates a generally moderate and positive relationship with emergence success, which is statistically significant in many of the models. For the full sample (1) and (2) and the sub-sample between 2011-2021 (6), leverage is significant at a 5% level and in model (4) and (7) at a 10% level. During 2011-2021 the positive influence of leverage on emergence success was particularly strong with a coefficient of 1.91. Moreover, the pre-filing **ROA** also is positively related to emergence success and statistically significant when analysing the sample as a whole with coefficients ranging from 0.69 to up to 2.08. However, the variable loses significance in the sub-samples. This is likely due to the much lower number of observations in the sub-sample which lowers statistical power. To continue, pre-filing **firm size** does not show a significant relationship with emergence success and the coefficients are small and vary in signs. Therefore, firm size does not seem to meaningfully impact a company's likelihood of emergence. When looking at the full sample, pre-filing asset **tangibility** has a strong positive effect on emergence, even at a 1% significance level, but similarly to ROA this effect disappears when looking at sub-samples and the coefficient even turns negative in model (6).

The industry condition, measured by the variable '**Pre-Filing Industry Distress**', indicates a moderately negative coefficient for most of the models, but shows no statistically significant relationship with emergence success. I also tested if industry distress at emergence would have a significant influence. However, the variable predicted emergence success perfectly and hence, was omitted from the model.

Table 3. *Emergence success - regression output*

Emerge Success	(1) Entire sample; no industry FE	(2) Entire sample; Industry FE	(3) 1980-2000; Industry FE	(4) 2001-2021; Industry FE	(5) 2001-2010; Industry FE	(6) 2011-2021; Industry FE	(7) 2001-2021; Industry FE
Pre-Filing Cash Ratio (log)	-0.02	-0.03	0.04	-0.02	-0.02	-0.42*	-0.01
	(0.04)	(0.05)	(0.12)	(0.05)	(0.06)	(0.22)	(0.06)
Pre-Filing Leverage (log)	0.88**	0.80**	0.55	0.93*	0.29	1.91**	1.19*
	(0.38)	(0.40)	(0.49)	(0.51)	(0.57)	(0.90)	(0.61)
Pre-Filing ROA	1.05**	1.03**	0.85	1.03	2.08	0.99	0.69
	(0.45)	(0.47)	(0.71)	(0.73)	(1.74)	(0.95)	(0.62)
Pre-Filing Firm Size (log)	-0.04	0.00	-0.03	0.02	-0.11	0.46	-0.25
	(0.11)	(0.11)	(0.24)	(0.16)	(0.19)	(0.45)	(0.17)
Pre-Filing Tangibility	1.97***	1.64***	1.55	0.65	1.27	-1.91	0.28
	(0.46)	(0.58)	(1.03)	(0.94)	(1.19)	(2.36)	(0.93)
Pre-Filing Industry Distress	-0.45	-0.53	0.08	-0.55	-0.72	-1.63	-0.56
	(0.33)	(0.35)	(0.67)	(0.46)	(0.59)	(1.21)	(0.53)
DIP Financing	0.20	0.11	-1.13**	1.34***	0.85	2.37***	1.22***
	(0.26)	(0.28)	(0.54)	(0.44)	(0.62)	(0.89)	(0.43)
Duration (log)	-0.74***	-0.82***	-0.57	-0.92***	-1.11***	-1.45	-0.96***
	(0.20)	(0.21)	(0.36)	(0.30)	(0.38)	(0.92)	(0.36)
Free-Fall	-1.14***	-1.03**	-1.55*	-0.99*	-1.10*	-0.39	
	(0.41)	(0.44)	(0.86)	(0.51)	(0.62)	(1.02)	
Prepack							0.31
							(1.05)
Pre-Negotiated							0.69
							(0.56)
Firm Sale	-1.35***	-1.36***	-0.91**	-1.85***	-1.49***	-3.16***	
	(0.28)	(0.28)	(0.45)	(0.42)	(0.55)	(1.18)	
Sale 363							-1.80***
							(0.56)
Sale Intended							-0.63
							(0.45)
CEO Replaced	4.09***	4.07***	4.63***	4.10***	4.46***	4.45***	4.66***
	(0.31)	(0.31)	(0.60)	(0.43)	(0.54)	(0.78)	(0.64)
Creditors' Committee	0.17	0.19	0.88	-0.34	-0.55	0.03	-0.03
	(0.39)	(0.40)	(1.08)	(0.59)	(0.73)	(1.21)	(0.67)
Equity Committee							-0.43
							(0.73)
Retiree Committee							-0.31
							(0.72)
Delaware Or New York	0.15	0.08	-0.69	0.67*	0.80	1.35**	
	(0.26)	(0.28)	(0.45)	(0.37)	(0.49)	(0.58)	
Delaware							0.51
							(0.44)
New York							1.25*
							(0.64)
Constant	4.04***	2.51*	2.78	4.78***	7.54***	5.54	5.85***
	(1.10)	(1.41)	(2.25)	(1.81)	(2.20)	(5.41)	(2.04)
Observations	709	709	252	448	305	143	419
Pseudo R2	0.52	0.53	0.54	0.58	0.61	0.65	0.63

Standard errors in parentheses * $p<0.10$ ** $p<0.05$ *** $p<0.01$

Regarding the bankruptcy process characteristics, **DIP financing** is associated with a strong positive statistically significant effect on emergence success in the second half of the sample, as indicated in models (4) and (6) with a coefficient well above 1 and p-values below 0.01. When looking at the two sub-samples of that period, while still moderately positive in model (5), only in the period between 2011 and 2021, model (6), the coefficient is statistically significant. Moreover, it indicates a very high influence on emergence success with a coefficient of 2.37. On the other hand, in the period between 1980-2000, model (3), the coefficient is -1.13 and significant at a 5%-level, implying a reversed relationship during that time frame. However, given that the first DIP financing case occurred in 1991, this coefficient should be disregarded. **Duration** has a consistently negative impact on emergence success with coefficients ranging from -1.45 to -0.57. Moreover, with the exception of models (3) and (6) duration is statistically significant at a 1%-level. **Free-Fall** bankruptcies also indicate a consistent negative relationship with emergence success, with coefficient ranging between -1.55 to -0.39. With the exception of the sub-sample from 2011-2021, model (6), all values are statistically significant. Having a pre-pack or pre-negotiated plan, on the other hand, shows a positive impact on the likelihood of emergence (model (7)). Nevertheless, these coefficients do not indicate a significant p-value. Similarly to duration and free-fall, **firm sale** also shows relatively high negative ecoefficiency across all models, ranging from -3.16 to -0.91. All of them are significant at least at a 5%-level. When splitting the variable in ‘Sale 363’ and ‘Sale Intended’, model (7), both indicate a negative coefficient, but only the one of ‘Sale 363’ is significant.

Regarding governance and legal features, **CEO** replaced appears to be one of the most robust predictors for emergence success. The variable shows a large positive coefficient of above 4, each being significant at a 1%-level, for all models. The presence of a **creditors’ committee**, however, does not show statistically significant impact in any of the models and indicates a small coefficient. When extending the model by the variables ‘Equity Committee’ and ‘Retiree Committee’ in model (7), all committees indicate a negative impact on the likelihood of emergence, in the period from 2000-2021, but none of them are statistically significant. Moreover, filing in **Delaware or New York** had a positive impact on emergence success, with exception of model (3). However, only the period 2001-2021 in model (4) and the sub-period 2011-2021 in model (6) show significant p-values. When splitting the variable into two independent binary indicators, ‘New York’ and ‘Delaware,’ for the time period 2001-2021, model (7), only ‘New York’ has statistically significant p-value ($p < 0.1$). However, both coefficients are still positive.

7.2. No refile within 5 years

The goal of the second regression analysis is to identify factors that influence the likelihood of a company to refile for bankruptcy within 5 years of emergence. I initially used the pre-filing financial and industry distress variables as I did for the emergence success analysis. However, given the time gap between refiling and the initial filing can be very long, most of these variables lost their predictive power. Therefore, I created a second version of them that measures the variables at emergence. Models (1) – (2) again follow my standard structure of using the entire sample period with and without industry fixed effects and as in the other regression analysis model (3) uses a time frame from 1980-2000. However, for model (4) I shortened the sample period to 2001-2017 as the dependent variable takes refiles into consideration of up to 5 years after emergence and I wanted to ensure that all variable measurements are completed. Moreover, due to the low number of observations because of insufficient data availability, I refrained from splitting the second time period into two smaller samples. Similarly to model (7) in the emergence success regression analysis I initially added an extension model base on the time frame 2001-2017, which further specified the 'Free-Fall', 'Firm Sale' and 'Delaware or New York' variables. However, the model indicated a substantial and unexplainable shift in several coefficients which likely reflected multicollinearity and overfitting, given the limited number of cases. Therefore, I decided to omit this model.

Compared to the first regression analysis the pseudo R2's are slightly lower. However, they still indicate a good fit with values ranging from 0.13 – 0.34.

Table 4. No refiling within 5 years - regression output

No Refiling Within 5 Years	(1) Entire sample; no industry	(2) Entire sample; Industry	(3) 1980-2000; Industry	(4) 2001-2017; Industry
Emergence Cash Ratio (log)	-0.00	-0.02	-0.10	0.81
	(0.14)	(0.13)	(0.14)	(0.75)
Emergence Leverage (log)	-0.34	-0.31	-0.49	-0.40
	(0.41)	(0.48)	(0.60)	(1.14)
Emergence ROA	-0.29	-1.56	-0.14	-2.08
	(1.80)	(2.21)	(3.17)	(6.52)
Emergence Firm Size (log)	0.32**	0.38**	0.26	-0.89
	(0.15)	(0.18)	(0.24)	(0.80)
Emergence Tangibility	0.32	-0.02	-2.37*	-0.06
	(0.78)	(0.88)	(1.36)	(1.57)
Emergence Industry Distress	0.70	0.49	-1.14	-0.27
	(1.01)	(1.18)	(1.79)	(1.74)
DIP Financing	0.07	0.53	-0.03	1.01
	(0.43)	(0.46)	(0.60)	(1.42)
Duration (log)	-0.33	-0.47	-0.32	0.11
	(0.31)	(0.38)	(0.50)	(1.10)
Free-Fall	1.17**	1.94**	1.42	18.46***
	(0.58)	(0.76)	(1.28)	(2.93)
Firm Sale	-0.09	0.03	0.75	-1.52
	(0.44)	(0.53)	(0.72)	(1.00)
CEO Replaced	-0.19	-0.21	0.17	0.00
	(0.55)	(0.62)	(0.75)	(.)
Creditors' Committee	0.68	0.68	0.46	0.77
	(0.66)	(0.72)	(0.88)	(1.83)
Delaware Or New York	-1.26**	-1.46***	-2.03***	-2.13*
	(0.55)	(0.56)	(0.66)	(1.11)
Constant	0.80	1.66	1.73	9.86
	(1.66)	(1.78)	(2.41)	(8.25)
Observations	205	196	120	61
Pseudo R2	0.13	0.22	0.27	0.34

Standard errors in parentheses * $p<0.10$ ** $p<0.05$ *** $p<0.01$

Starting with the financial indicators the regression analysis indicates that the **cash ratio** at emergence does not seem to have a clear relationship with the refiling rate. The coefficients are rather small, positive and negative and insignificant. The **leverage** ratio at emergence has a negative coefficient consistently between -0.3 and -0.5. While none of the values reach the significance threshold, the direction is stable. This suggests a tendency for highly levered firms to refile. The emergence **ROA** also has a consistent negative coefficient ranging from -0.14 to -2.08 in models (1) – (4). This indicates that the higher the ROA, the higher the chance of refiling. However, again, none of the values are significant. When looking at the entire sample, the emergence **firm size** coefficients are slightly positive and models (1) and (2) even indicate statistically significant values, implying that larger companies are more likely to avoid refiling. However, in later sub-samples these effects disappear, and the coefficients become smaller and even turn negative. **Asset tangibility** shows a tendency for a negative relationship with the 'No Refiling Within 5 Years' variable. When assigning industry fixed effects, all models show negative coefficients. Nevertheless, only model (3) has a significant coefficient of -2.73, meeting the p-value below 0.1 threshold.

Moving on to the industry conditions at emergence, similar to the emergence success regression analysis, **industry distress** does not seem to be a significant predictor for refiling. The coefficients don't indicate a clear direction, neither are they significant.

Regarding the bankruptcy process characteristics, the use of **DIP financing**, the **duration** and whether or not a **firm sale** occurred as part of the reorganisation, also fail to show a consistent or significant relationship with refiling risk. The **'Free-Fall'** variable on the other hand indicates a strong positive relationship with refiling risk, implying that companies which file as a free-fall are more likely to refile again within 5 years. The coefficients range from 1.17 to an extremely high and significant value ($p < 0.05$) of 18.46 in model (4). The coefficients of models (1) and (2) are also both significant at a 10% level.

Regarding governance and legal features, **replacing the CEO** during the reorganization does not have a significant effect on the refiling risk. When looking at the impact of **creditors' committees**, even though the coefficients are not significant, they do indicate moderate positive relationship with refiling. Finally, companies that file in in **Delaware or New York** are significantly more likely to refile again within five years. All models show rather high negative and statistically significant coefficients, ranging from -1.26 to -2.13.

7.3. EBITDA sign change

In my final regression analysis, I tried to identify if the variables have a significant impact on operating performance improvements, measured as a sign change from negative to positive in EBITDA. As for the refiling risk analysis I used financial and industry measures at emergence. Moreover, given the high conceptual overlap between ROA and EBITDA, I excluded the ROA variable in all models. Regression models (1) – (4) again follow the standard structure. Model (1) and (2) include the entire sample size, once without industry fixed effects and once with industry fixed effects. Model (3) uses a sample period from 1980 to 2000 and model (4) 2001 to 2021, both including industry fixed effects. Similarly to the refiling regression analysis, due to a low number of observations it did not make sense to split the data into further sub-samples. Model (5) is an extension of model (4) including the variables ‘Prepack’ and ‘Pre-negotiated’ instead of ‘Free-Fall’ and the variables ‘Delaware’ and ‘New York’ instead of ‘Delaware or New York’. I also added the variables ‘Equity Committee’ and ‘Retiree Committee’. The pseudo R2s are relatively low for models (1) to (3) but reach 0.24 and 0.29 in models (4) and (5), indicating some predictive power.

Starting with the financial variables, only the emergence **cash ratio** is a consistent and statistically significant predictor of sign change improvements in EBITDA. The coefficients of the variables are positive and stable in all models ranging from 0.28 to 0.58. When looking at the full sample period, models (1) and (2), the values are also statistically significant at a 5% and 10% level, respectively. The **leverage** coefficients do not indicate a stable pattern, ranging from -0.33 to 0.05 and none of the values are statistically significant, indicating that leverage at emergence is no predictor of EBITDA change. The same holds for **firm size** with insignificant coefficients ranging from -0.46 to 0.15, implying that firm size has no predictive power for the likelihood of a positive sign change in EBITDA. For **asset tangibility** the coefficients again switch signs in between models and are insignificant.

Industry distress at emergence has a consistently negative coefficient. Especially in the 2000-2021 sub-sample, model (4) and (5), the coefficients are relatively large with -1.88 and -2.47. Both values are also significant on a 10% level. Therefore, industry wide distress at the time of emergence seems to decrease the likelihood of achieving a sign change in EBITDA from negative to positive.

__Table 5.__ EBITDA sign change - regression output

EBITDA Sign Change	(1) Entire sample; no industry FE	(2) Entire sample; Industry FE	(3) 1980-2000; Industry FE	(4) 2001-2021; Industry FE	(5) 2001-2021; Industry FE
Emergence Cash Ratio (log)	0.38**	0.35*	0.28	0.42	0.58
	(0.17)	(0.18)	(0.25)	(0.36)	(0.50)
Emergence Leverage (log)	-0.06	0.05	-0.09	-0.33	0.05
	(0.35)	(0.36)	(0.48)	(0.66)	(0.80)
Emergence Firm Size (log)	-0.07	-0.06	0.15	-0.38	-0.46
	(0.11)	(0.12)	(0.18)	(0.32)	(0.45)
Emergence Tangibility	0.99	0.61	-0.80	2.64	3.11
	(0.65)	(0.74)	(1.11)	(2.01)	(2.47)
Emergence Industry Distress	-0.08	-0.18	-0.01	-1.88*	-2.47*
	(0.60)	(0.70)	(0.91)	(1.09)	(1.30)
DIP Financing	-0.11	-0.14	-0.01	-0.96	-1.50
	(0.35)	(0.37)	(0.56)	(0.83)	(1.10)
Duration (log)	-0.21	-0.17	-0.16	-0.15	-0.90
	(0.24)	(0.26)	(0.36)	(0.47)	(0.75)
Free-Fall	0.51	0.54	0.86	0.61	
	(0.49)	(0.52)	(0.80)	(0.71)	
Prepack					-0.33
					(1.76)
Pre-Negotiated					-0.54
					(0.80)
Firm Sale	0.13	-0.00	0.45	-0.42	-0.95
	(0.33)	(0.34)	(0.51)	(0.60)	(0.66)
CEO Replaced	0.04	0.32	0.14	-0.11	-0.15
	(0.43)	(0.47)	(0.68)	(0.71)	(0.77)
Creditors' Committee	1.03*	1.07**	0.42	1.87**	3.07**
	(0.55)	(0.54)	(0.74)	(0.83)	(1.25)
Equity Committee					1.30
					(1.26)
Retiree Committee					4.50***
					(1.25)
Delaware Or New York	-0.38	-0.36	-0.34	-0.52	
	(0.35)	(0.38)	(0.52)	(0.74)	
Delaware					-0.44
					(1.00)
New York					-1.96
					(1.20)
Constant	0.81	-0.38	1.41	0.98	5.46
	(1.42)	(1.54)	(2.13)	(2.40)	(3.73)
Observations	200	199	121	75	75
Pseudo R2	0.08	0.12	0.14	0.24	0.29

Standard errors in parentheses * p<0.10 ** p<0.05 *** p<0.01

Regarding the bankruptcy process characteristics, the '**Duration**' variable shows consistent negative coefficients, implying a weak positive relationship with a sign change in EBITDA. However, none of the values are statistically significant. The '**Free-Fall**' variable also has no coefficients in any of the models that meet the statistically significance threshold, but all coefficients are positive, which indicates a weak tendency for a positive relationship with the dependent variable. Additionally, the extension in model (5), which includes the variables

‘Prepack’ and ‘Pre-negotiated’ shows slightly negative coefficients for both. This finding further supports the argument that the variable ‘Free-Fall’ has slight predictive powers. Moreover, the ‘**Firm Sale**’ variable does not indicate a significant impact on the EBITDA performance. None of the coefficients are significant and they are not consistent with their sign. The same is holds for the variable ‘**CEO replaced**’.

Establishing a **creditors’ committee** is strongly positively related to a sign change in EBITDA performance with consistent positive coefficients between 1.04 and 3.07. With the exception of model (3) all of the values are statistically significant at least at the 10% level. Model (5) also indicates positive coefficients for the variable’s equity committee and retiree committee, 1.3 and 4.5 respectively. Moreover, the retiree committee coefficient is statistically significant at a 1% level. Finally, the variable ‘Delaware and New York’ does not indicate significant prediction power.

8. Results

This section synthesizes the findings across all three dependent variables to highlight which variables exhibit strong predictive power. As anticipated, the models using ‘Emergence Success’ as the dependent variables yielded the most consistent and statistically significant predictors. This is likely due to the larger sample size, which provides greater statistical power and stability in estimation coefficients. The models predicting the likelihood of refiling within five years and of a positive sign change in EBITDA, rely on a much smaller sample size, which explains the greater variability in predictive outcomes and weaker predictive power. Nevertheless, the models are still valuable and help to explain the relationship and tendencies of many variables.

Starting with the **cash ratio**, based on the study by Flynn (1998), I expected the ‘Cash Ratio’ variable to have a significant positive effect on the success of a Chapter 11 process due to higher liquidity. However, my regression results indicate that cash only has a statistically moderate impact on one of the dependent variables, the positive EBITDA sign change. The consistent positive coefficients are in line with existing literature. Cash-rich companies have a higher likelihood to turn their negative EBITDA into a positive one. This is likely due to liquidity provided by the cash, which enables companies to operate more flexible during the restructuring activities. Furthermore, companies with higher cash reserves can use their cash for investments that are targeted to turn around and improve operations.

Regarding leverage the regression output indicates that companies that are **highly levered** have a significant higher probability of emerging from Chapter 11 across the entire sample. In contrast to that, even though not statistically significant, the results also indicate a trend for highly levered firms to refile again. These findings seem contradictory at first but are well in line with existing literature. As mentioned by LoPucki and Doherty (2005), Chapter 11 is designed to fix companies with financial distress, which is the result of excessive leverage, not those with economic distress. Therefore, companies with high leverage, benefit from deleveraging during the process, which increases their likelihood to emerge and therefore explain the positive relationship with emergence success. However, if companies are still overleveraged at the point of emergence they have a higher likelihood of refiling, as mentioned by Altman (2009). This explains the negative tendency the coefficients in the refiling regression analysis.

Regarding the **ROA**, based on Li and Wang (2016) I expect ROA to be positively related to Chapter 11 success, as a stronger operating performance makes it easier for companies to execute their reorganisation plan and to secure financing. My results for emergence success support this hypothesis and show that companies with higher ROA ratios significantly increase the likelihood emerging from Chapter 11. Interestingly, even though not statistically significant, when it comes to the refiling rate, higher ROA tend to increase the chance of refiling in my regression analysis, which contradicts Li and Wang's (2016) findings. Possible explanations for this are that temporary improvements in performance around emergence are short lived and may not be sustained in the long run, leading to future re-filings. Furthermore, higher ROA may lead to firm emerging prematurely with lingering structural weaknesses. In addition, the higher ROA may be artificial and as a direct impact of potential DIP financing during the Chapter 11 Process. This may over-emphasise the financial stability of the business immediately upon emergence. Therefore, ROA is a strong short-term signal of viability, explaining the positive relationship with emergence, but not a guarantee of long-term success.

Opposite, to Hotchkiss's (1993) study, which found that larger firms are more likely to emerge from a Chapter 11 because they have an advantage over smaller firms as they have more assets to divest, my regression analysis indicates that **firm size** has no predictive powers to assess the probability of emergence. In my regression analysis on the ability to turn a negative EBITDA into a positive one I have the same results. When analysing the impact of firm size on the likelihood of refiling a moderate and significant relationship shows. This implies that larger companies are less likely to refile. This can be explained by their greater access to restructuring resources and diversified operations. Interestingly, for the sub-sample of 2001-2017 the coefficient is negative. However, the coefficient is not significant and the model has a very small sample size, with only 61 observations for a time span of 17 years. On top of that, the time span included the 2008 crisis which has likely led to negative outliers.

Opposite to Ayotte and Morrison (2009) finding, that high asset **tangibility** decreases the of emergence, due to a higher a higher proportion of secured creditors that push for liquidation, I found an overall significant and positive relationship between asset tangibility and the emergence probability. While these results agree with the first part of Ayotte and Marrison's (2009) argument that higher tangible assets allow firms to secure more financing, my results suggest that this financing helps companies to reorganize their operations instead of leading to liquidation. Furthermore, courts might also be more willing to support a reorganization when high amounts of salvageable tangible assets are available, which would also explain the associated higher emergence rates. Interestingly, in the sub-sample 2011-2021, even though not significant, the coefficient is strongly negative. This might indicate an overall economic shift towards intangible assets, making tangibility less relevant. Additionally, as Private Equity LBOs became more prevalent, it may be contended that lenders would be more inclined to accept restructuring terms from sponsors to continue close relationships rather than seeking liquidations of businesses with significant PP&E. Moreover, the increasing use of prepacks and 363 sales might drive outcomes more than balance sheet asset quality. Therefore, the strong predictive power of assets on emergence success might start to deteriorate. When looking at the likelihood of refiling, the regression output indicates that there is a tendency for companies with high asset tangibility to refile within five years. This finding contradicts with existing literature. A possible explanation for the finding is that tangible-heavy firms might carry a structural disadvantage including asset inflexibility, capital intensity and limited adaptability. This might in turn increase their chances of re-entering bankruptcy even though their reorganized balance sheets seem solid.

Surprisingly, neither with regards to emergence success nor to the refiling probability does **industry distress** seem to play an important role. Based on previous literature and the descriptive statistic that clearly followed economic trend, I would expect the industry conditions to have quite significant predictive powers. However, only in the EBITDA sign change models, the variable's coefficient indicates a decreased likelihood of turning around operational performance in times of industry wide distress. Companies operating in struggling sectors already face numerous challenges e.g., weak-demand and constrained growth opportunities. This likely hinders their ability to improve operational performance.

In line with previous studies, **DIP financing** has a strong and significant positive relationship with emergence success. Therefore, my findings support Dahiya's et al. (2003) argument that companies that receive DIP financing indicate their ability to potential creditors that they can emerge quickly. What seems counterintuitive at first is that my results show consistent negative coefficients, though not significant and rather small, when regressing DIP financing against EBITDA improvements. An explanation could be that DIP-backed restructurings frequently emphasise creditors' recovery and quick emergence, potentially at the expense of operational improvements. An additional consideration is that a significant portion of DIP financing may be used to pay advisor fees during the process.

My study finds that longer **duration** strongly decreases the likelihood of emerging, with most coefficients being negative on a 1% level. This at first glance, seems to contradict Warren and Westbrook (2009), who found that successful cases tend to spend more time in Chapter 11, than unsuccessful ones because Chapter 11 is designed to dispose losers as soon as possible. However, the authors finding is based on average case duration, while my regression identifies a marginal negative effect of longer duration, controlling for firm characteristics. Overall, as Warren and Westbrook (2009) established, successful cases may take longer on average than failures. My study goes a bit further and shows that longer duration itself is not necessarily helpful e.g., due to an accumulation of costs, operational disruptions and loss of stakeholder trust. This can also explain the weak tendency of longer durations to negatively impact EBITDA improvements. Longer Chapter 11 filings might shift the focus from performance to procedural survival. Moreover, based on my results, duration does not impact the probability of refiling.

I found strong evidence that **free-falling** cases are much more likely not to emerge from Chapter 11. This finding is rather intuitive and in line with previous literature as LoPucki and Doherty (2015) found that companies which file a prepack or pre-negotiated plan are more likely to survive. This indirectly implies that free-fall cases are less likely to survive. Interestingly, I also found a positive relationship between companies' probability to avoid refiling. This could imply that companies which manage to emerge despite being a free-fall case undergo a more comprehensive reorganisation, which in turn makes the company stronger and more stable in the long run. While not statistically significant, the trend that free-fall cases have an increased likelihood of achieving a positive sign change in EBITDA supports this argument.

Regarding the impact of **firm sales** on success of Chapter 11 filings only for the emergence success measure was observed to be a significant predictive power. The results indicate a strong negative relationship between firm sale and the probability of emergence. To understand this finding it is important to keep in mind that for a company to emerge it needs to continue to exist as an independent entity, which can either be through a reorganization or as part of a 363 However, assets or business unit sales during Chapter 11 often result in liquidation or integration into the buyer. Therefore, the distressed firm no longer acts as a standalone company, explaining the high likelihood of failing to emerge in case a sale occurs. The strongly negative and significant coefficient for the 363 sale variable in the extended model further supports this finding.

My study identifies **CEO replacement** is the strongest predictor for emergence success. All coefficients are greater than 4 and significant on a 1% level. This is in line with the finding of Lin et al. (2020) that CEO turnover significantly improves probability of emerging, explained by an improvement in managerial expertise to drive the restructuring process and a reduction in management entrenchment. CEO replacement does not significantly influence the refiling rate or probability of improvements in EBITDA.

While Harner and Marinic (2011) found that cases with a **creditors' committee** are more likely to result in a liquidation than emergence, my results don't indicate any predictive power for the emergence probability. However, my findings to indicate a tendency for companies with creditor committee in place, even though not statistically significant, no to refile for bankruptcy. Furthermore, creditors' committees are the independent variable with the highest predictive power regarding the EBITDA improvement variable. More specifically, cases with a creditors' committee in place are much more likely to turn a negative EBITDA into a positive EBITDA. Therefore, while Harner and Marinic (2011) highlight a tendency towards liquidation if a creditors' committee is established, my findings suggested that if the firm achieves emergence, creditors' committees' involvement supports a more sustainable restructuring. The extended regression model also shows that having a retiree committee in place significantly improves the likelihood of achieving improvements in EBITDA.

Overall, even though the evidence is rather weak, my study suggests that companies that file in **Delaware or New York** have a slightly higher probability of emerging. When splitting the variables for the time frame 2001 – 2021, only New York stays significant. Furthermore, the 'Delaware or New York' variable is the strongest indicator for refiling in my regression analysis. My study shows that companies which file in either of those cities are very likely to refile again. This supports the argument by LoPucki and Doherty (2015) that the laissez-faire approach by these courts increase the chances of emerging, but at the same time also increase the likelihood of refiling because many plans are confirmed too quickly and without sufficient consideration.

9. Robustness

To ensure the validity and reliability of the regression results, I conducted several robustness checks. First, as already mentioned, all regressions were estimated using the "robust" command in Stata. Furthermore, every regression analysis includes at least four models which are controlled for heterogeneity across industries. This inclusion did not substantially change my results, confirming the robustness of the models.

Given the long timespan of the sample, the creation of sub-samples accounts for potential changes in the bankruptcy environment over time. The inclusion of alternative specifications of certain variables such as differentiating between prepackaged and pre-negotiated cases, allowed me to test if broad definitions inflate the results. Moreover, I analysed pairwise correlation to ensure that independent variables are not heavily correlated. This increases the stability of the model (see appendix – Table A1).

To assess if the some of the variables depend on the level of another, I extended my models by including interaction terms for variables where I expected meaningful relationships. More specifically, I included interaction terms between ROA and DIP financing, case duration and free-fall status and ROA and CEO turnover. I tested the interaction variables across all three success measures. However, due to the small sample size for the variables 'No refiling within 5 years' and 'EBITDA sign change' some of the interaction terms were omitted in the analysis due to perfect prediction and collinearity. Therefore, I focused on the emergence success model outputs (see appendix – Table A2). None of the interaction terms were statistically significant across any of the models. This highlights that the effects of the main variables are not strongly dependent on the interaction conditions, further supporting the robustness of the baseline model.

On top of applying a log transformation to heavily skewed variables such as size, leverage and duration, to ensure that they did not lead to misleading results, I created dummy variables based on percentile thresholds (e.g., top 25% and lowest 25%). However, the results remained directionally consistent.

10. Limitations

Despite the valuable insights the study provides, several limitations must be acknowledged. Most importantly, the analysis is constrained by **limited data availability.** Many firms do not report detailed financial information at the time of emergence. Therefore, many cases for the refiling and EBITDA regression analysis are incomplete, explaining the low number of observations. This weakens the statistical power of the models and may lead to biases towards firms with more complete disclosures, which are typically larger companies. Additionally, the number of observations in early years of the sample period is rather low with many years only containing a few cases. This makes it difficult to detect robust time trends. Moreover, the dataset only includes large public companies. That significantly **limits the generalizability** of the findings on smaller or private companies. Furthermore, all dependent variables are binary indicators. This approach may **oversimplify** the nuances of different success levels. Particularly for the EBITDA variable the approach might lead to flawed interpretation. Companies that have a positive EBITDA at filing and further increase this EBITDA throughout the process still technically are not considered to have succeeded on operating performance level.

11. Conclusion

This paper aims to identify factors that influence the success of Chapter 11 filings. Given the broad difference in significant predictors across the three models, it becomes clear that success is not a uniform concept in the context of Chapter 11. While some independent variables have high predictive powers for one success measure, they might not have any significant influence on another measures. In some cases, even the direction of prediction is reversed. Emergence success seems to capture short-term procedural success. In contrast, avoiding refiling for the five years following emergence reflects long-term viability as the result of a sustainable reorganization. Achieving a positive sign change in EBITDA on the other hand, points to operational improvements. Overall, the variables 'DIP financing', 'Duration', 'Free-Fall' and 'Firm Sale' and 'CEO Replacement' are the strongest predictors for emergence success. The refiling rate is mostly influenced by the variables 'Emergence Firm Size', 'Free-Fall' and the filing venue ('Delaware or New York'). 'Creditors' Committee', 'Emergence Cash Ratio' and 'Emergence Industry Distress' are the variables which indicate the highest predictive power for a positive sign change in EBITDA. While not statistically significant, 'Duration' and 'Free-Fall' also consistently show clear and directional effects the EBITDA models. This makes 'Free-Fall' the only independent variable with some level of predictive influence across all three success dimensions.

The main findings can be summarised as following:

1. **Larger companies are less likely to refile for bankruptcy** within five years of emergence. This is likely the result of their greater access to restructuring resources and diversified operations.
2. **Companies that are highly levered have a higher probability of emerging but tend to refile.** This can be explained by differentiating between financial distress and economic distress. Companies with high leverage benefit from deleveraging, which is a cornerstone of Chapter 11, those that are in economic distress don't. Furthermore, if still overleveraged at the point of emergence they tend to refile.
3. **Companies with higher ROA are significantly more likely to emerge,** as their stronger operating performance makes it easier for the companies to execute their reorganisation.
4. **Higher tangibility of assets increases the likelihood of emergence.** This is likely the result of companies with higher tangibility of assets being able to secure more financing.

5. **Industry distress at emergence lowers the probability of a company being able to turn a negative EBITDA in to a positive one.** On top of firm specific challenges, the companies need to deal with a broader economic downturn further weakening their ability to improve their operational performance.
6. **Companies that receive DIP financing are significantly more likely to emerge**, than companies that don't. This supports the idea of DIP lenders having a screening role in which they provide liquidity to the companies with the greatest emergence potential and support a quicker and more efficient reorganization.
7. **Cases with high duration have a significantly higher likelihood of failing to emerge.** Furthermore, duration also has a tendency to negatively impact the probability of achieving a positive sign change in EBITDA. These results can be explained by the high accumulation of costs, operational disruptions and erosion of stakeholder trust associated with long reorganization procedures.
8. **Free-fall cases are significantly less likely to emerge from Chapter 11, but if they emerge, they have a much higher likelihood of avoiding refiling**, than prepackaged or pre-negotiated filings. They also tend to achieve a positive sign change in EBITDA. This suggests that free-fall bankruptcies are risky in the short-term, but if emergence is achieved, they often lead to more sustainable reorganization.
9. **Cases that engage in asset sales during the reorganisation are much less likely to emerge** from Chapter 11. This seems rather logical as emergence implies that the company continues to operate independently, which is often not the case if a large asset sale occurs.
10. **Changing the CEO during a Chapter 11 filing materially increases the probability of emerging**, as it often brings in leadership better suited to drive the restructuring process and decreases management entrenchment.
11. **Cases with a creditors' committee in place are much more likely to turn a negative EBITDA into a positive one** throughout the Chapter 11 process, indicating that creditor involvement supports a more sustainable development.
12. Overall, **companies that file in Delaware or New York have a slightly higher probability of emerging but are significantly more likely to refile**. This is explained by the laissez fair approach in those two locations that allow a lot of companies to emerge but at the same time means that many plans are not well thought through.

These findings carry several important implications for bankruptcy policies and practices. First, the strong positive relationship between DIP financing and emergence success highlights the need to facilitate DIP lending on a larger scale. The regulator could implement mechanisms that encourage creditors to provide more DIP capital e.g., through practical guarantees and clearer seniority rules. Furthermore, given the negative impact of free-fall cases on emergence success, the regulator should develop more structured guidelines for free-fall filings. These should be based on successful free-fall emergences as this would simultaneously decrease refiling rates. Moreover, given the positive effect of creditors' committees on operational turnaround, courts should start to promote the formation of such committees as part of the reorganisation plan confirmation. Finally, to reduce the high refiling rate of cases filed in Delaware or New York, the plan confirmation standards should become stricter and venue shopping should be limited.

To further deepen our understanding on factors that influence Chapter 11 success, it would be interesting to explore how outcomes differ-across sectors. Since companies in different sectors differ in many factors such as asset structure, capital intensity and operations. Better understanding individual sectors would also help to draw conclusions on general Chapter 11 behaviour. Furthermore, my research has established that different success measures vary in terms of indicating how sustainable the reorganization is in the long run. On top of analysing the refiling rate up to five years of emergence it would be interesting to also assess how operating performance or stock prices develop over a similar time horizon. Moreover, it would be extremely interesting to construct a success measure that is based on recovery rates as this is the major concern for creditors. Finally, investigating how the predictive power of key variables changes during major economic shocks, such as during the COVID-19 pandemic or the 2008 crisis, could allow us to make companies more crisis resistant.

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13. Appendix

Table A1. *Correlation matrix*

	ln_Cash_10K	ln_Cash_Eme	Ln_Leverage_	Ln_Leverage_	ROA_10KBef	ROA_Emergi	Tangibility_1	Tangibility_E	IndDistress_1	IndDistress_E	DIP_Financin	ln_Duration	FreeFall	Sale_Happene	Ceo_Change	Creditors_Co	Delaware_or_N
ln_Cash_10KBefore	1	0.561	0.047	-0.097	-0.183	0.005	0.028	-0.010	0.112	0.098	-0.168	-0.017	0.028	-0.044	0.129	-0.021	-0.087
ln_Cash_Emerging	0.561	1	-0.082	-0.216	-0.071	0.072	0.055	-0.008	0.153	0.112	-0.180	0.182	0.175	0.035	-0.006	0.127	-0.007
Ln_Leverage_10KBefore	0.047	-0.082	1	0.147	-0.112	0.054	-0.010	-0.086	0.064	-0.059	0.116	-0.215	-0.230	0.027	-0.038	-0.195	0.137
Ln_Leverage_Emerging	-0.097	-0.216	0.147	1	-0.001	0.093	0.072	0.289	0.031	-0.022	0.028	-0.080	-0.159	0.152	-0.011	-0.089	-0.094
ROA_10KBefore	-0.183	-0.071	-0.112	-0.001	1	0.332	-0.097	-0.042	-0.229	-0.242	0.023	0.140	0.008	-0.043	0.101	0.126	-0.068
ROA_Emerging	0.005	0.072	0.054	0.093	0.332	1	0.227	0.221	-0.203	-0.190	-0.060	0.135	0.122	0.008	0.059	0.125	-0.096
Tangibility_10KBefore	0.028	0.055	-0.010	0.072	-0.097	0.227	1	0.746	-0.053	0.088	-0.126	0.012	0.025	0.151	-0.112	-0.019	-0.218
Tangibility_Emerging	-0.010	-0.008	-0.086	0.289	-0.042	0.221	0.746	1	0.036	0.237	-0.187	-0.048	-0.101	0.134	-0.065	0.019	-0.124
IndDistress_10KBefore	0.112	0.153	0.064	0.031	-0.229	-0.203	-0.053	0.036	1	0.317	-0.001	-0.020	-0.056	0.073	-0.011	0.089	0.125
IndDistress_Emerge	0.098	0.112	-0.059	-0.022	-0.242	-0.190	0.088	0.237	0.317	1	-0.105	-0.061	-0.080	0.127	-0.024	-0.008	0.089
DIP_Financing	-0.168	-0.180	0.116	0.028	0.023	-0.060	-0.126	-0.187	-0.001	-0.105	1	-0.047	-0.038	-0.043	0.060	-0.050	0.274
ln_Duration	-0.017	0.182	-0.215	-0.080	0.140	0.135	0.012	-0.048	-0.020	-0.061	-0.047	1	0.780	0.131	0.127	0.647	-0.274
FreeFall	0.028	0.175	-0.230	-0.159	0.008	0.122	0.025	-0.101	-0.056	-0.080	-0.038	0.780	1	0.099	0.089	0.540	-0.288
Sale_Happened	-0.044	0.035	0.027	0.152	-0.043	0.008	0.151	0.134	0.073	0.127	-0.043	0.131	0.099	1	-0.005	0.086	-0.049
Ceo_Change	0.129	-0.006	-0.038	-0.011	0.101	0.059	-0.112	-0.065	-0.011	-0.024	0.060	0.127	0.089	-0.005	1	0.044	-0.026
Creditors_Committee	-0.021	0.127	-0.195	-0.089	0.126	0.125	-0.019	0.019	0.089	-0.008	-0.050	0.647	0.540	0.086	0.044	1	-0.198
Delaware_or_NewYork	-0.087	-0.007	0.137	-0.094	-0.068	-0.096	-0.218	-0.124	0.125	0.089	0.274	-0.274	-0.288	-0.049	-0.026	-0.198	1

Table A2. Emergence success with interaction terms

	(2)	(3)	(4)
Emerge Success	Entire sample; Industry FE	1980-2000; Industry FE	2001-2021; Industry FE
Pre-Filing Cash Ratio (log)	-0.02	0.05	-0.02
	(0.05)	(0.11)	(0.05)
Pre-Filing Leverage (log)	0.82**	0.63	0.92*
	(0.41)	(0.49)	(0.51)
Pre-Filing ROA	1.18*	2.00	0.89
	(0.68)	(2.85)	(0.70)
Pre-Filing Firm Size (log)	-0.01	-0.09	-0.01
	(0.11)	(0.26)	(0.16)
Pre-Filing Tangibility	1.70***	1.67	0.65
	(0.58)	(1.05)	(0.94)
Pre-Filing Industry Distress	-0.52	0.02	-0.49
	(0.35)	(0.68)	(0.46)
DIP Financing	0.17	-1.09**	1.43***
	(0.29)	(0.55)	(0.46)
Duration (log)	-1.06**	-0.66	-0.96
	(0.52)	(0.47)	(0.67)
Free-Fall	-2.80	-2.79	-1.47
	(2.86)	(3.90)	(3.67)
Firm Sale	-1.35***	-0.91**	-1.86***
	(0.28)	(0.45)	(0.43)
CEO Replaced	4.02***	4.57***	4.13***
	(0.32)	(0.59)	(0.45)
Creditors' Committee	0.21	0.91	-0.33
	(0.42)	(1.16)	(0.62)
Delaware Or New York	0.07	-0.65	0.68*
	(0.28)	(0.44)	(0.38)
DIP Financing=1 # Pre-Filing ROA	1.49	1.30	2.10
	(1.45)	(5.38)	(1.39)
Free-Fall=1 # Duration	0.33	0.21	0.09
	(0.54)	(0.62)	(0.69)
CEO Replaced=1 # Pre-Filing ROA	-0.46	-1.40	0.45
	(0.82)	(2.90)	(2.42)
Constant	3.91	3.67	5.19
	(2.77)	(3.08)	(3.47)
Observations	709	252	448
Pseudo R2	0.53	0.54	0.59

Standard errors in parentheses * p<0.10 ** p<0.05 *** p<0.01