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Duration of a bankruptcy trial and the value of the firm: An empirical research for the United States of America

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Résumé

Le nombre d'entreprises qui font faillite aux États-Unis est en hausse depuis 1980. En nous basant sur le fait qu'il existe deux façons de déclarer faillite aux États-Unis, nous menons une analyse sur la duration du procès de faillite et son lien quant à la performance post-faillite d'une entreprise. Nous analysons plusieurs variables qui caractérisent le succès d'un procès et la manière dont la duration du dit procès les affectent. Nous voyons que plus un procès est long, moindre sont les chances de succès, et, que pour les entreprises qui réussissent, la durée du procès a un impact non négligeable sur les états financiers de l'entreprise. À travers l'utilisation de régressions OLS et Logistique, ainsi que l'utilisation d'une variable instrumentale, nous discussons l'implication qu'un procès plus long induit des coûts plus hauts ainsi que moins d'opportunités de réussite. Enfin, nous amenons un nouvel instrument pour estimer l'effet causal de la durée d'un procès sur le Chapitre 11.

Mots clés : Faillite ; Durée ; Pré-pack ; OLS ; Logistique ; Chapitre 11.

Abstract

Filings for bankruptcy in the USA has been on the rise since 1980. Based on the knowledge that there exists two ways to file for bankruptcy there, we lead an analysis of the duration of a bankruptcy trial on the success of a trial and its link to the post-bankruptcy performance of the company. We look at several dependent variables which characterize success in a bankruptcy trial and how duration has affected these values. Analysis shows us that the longer a trial is, the less chance there is that it will succeed and, even when it does, the longer cases have impeded the financial outlook of these companies. Through the use of OLS and Logit regression, followed by instrumental variable models, we discuss the implication that a longer trial might imply higher costs and less opportunity for emergence. Finally we implement a novel instrument to estimate the causal impact of duration on Chapter 11.

Keywords : Bankruptcy; Duration; Prepack; OLS; Logit; Chapter 11.

Table of Contents

I. Introduction.

Bankruptcy corresponds to a legal proceeding through which people or companies who are no longer in a position to pay their debts can get a sense of renewal by either creating a repayment plan or liquidating all their assets. In the United States, all bankruptcies rules and regulations are written in the '*Bankruptcy Code'* which is coded under federal law. For the case of companies, there exists two different ways to file for a bankruptcy. As a matter of fact, a company can file under Chapter 7 or Chapter 11.

Chapter 7 only pertains to liquidation. It is the Chapter that provides for the liquidation of all assets of an industry meaning that there is no hope for the re-emergence of the company. Under this chapter, a trustee is appointed to take care of the distribution of all the assets of the company; at the end of the distribution, a discharge is given to the owner of the company to fully free him from the debt. Consequently, for the purpose of our research, we will be focusing solely on Chapter 11 cases. Indeed, our research focuses on the possibility of re-emergence of the company which is an aspect that Chapter 7 does not take into consideration.

Chapter 11 allows for the creation of a plan of repayment under which the company will be repaying its debt with the help and guarantee of the Court. It can be a longer process because it involves the creation of a plan of repayment that has to be approved by all sides and followed thoroughly. Furthermore, this Chapter also implies that the company may have a chance to emerge back from its bankruptcy position; nonetheless, it is important to note that not all Chapter 11 cases are successful.

Previous research papers have been written trying to link the duration of a trial with the reputation of the judge as Schoar (2007), or even trying to look at the reallocation of assets comparing both Chapter 7 and 11 like Bernstein (2018). The papers of interests are the ones which have reviewed duration as a relevant variable for the success of a bankruptcy trial. As a matter of fact, given that Chapter 11 might be a lengthy process that allows for the re-emergence of a firm, we can therefore ask ourselves whether it is an important variable in the measure of success for a bankruptcy trial and if it has any impact on the post-reorganization performance of the company. Notwithstanding, it is crucial to underline that Chapter 11 does allow for the liquidation of all assets owned by the company but its main difference with Chapter 7 is that the liquidation is not a forced process.

The purpose of this paper is to answer the following question: "Is duration a relevant variable in the measure of success for a bankruptcy trial and does it impact the post-bankruptcy performance of the company?" To achieve this aim, we will try to build models that will verify the hypothesis that there exists a link between our variables and that there is a real relationship between the predictors and the response variable. From a starting standpoint, we hypothesize that there is a negative relationship between duration of a trial and its success as we theorize that shorter durations imply a better pre-negotiation of asset reorganization. We use several models to verify this hypothesis and come to the conclusion that it is indeed negatively related to the success of a trial. Furthermore, for companies who were able to emerge back we find that there is a negative relationship with success in their reorganization and the length of a trial, which hints on previous literature stating that duration can be used as a proxy for indirect bankruptcy costs. We understand that higher costs imply less money to reorganize itself, thus leaving the company with less performing financial ratios compared to firms that did not undergo bankruptcy filings. While it might be true that a longer duration might imply more arguments and more people involved, these positive outlooks on the duration of a trial are quickly outweighed by the importance of the costs that they imply. As such, our primary vision is to estimate a negative relationship between the duration of a trial and its success. We also look at a sector-based analysis, positioning ourselves using the Altman's Z-score on manufacturing VS non-manufacturing firms to estimate the effect of duration. As imagined, duration is longer for companies that are bigger in size, which is usually the case for manufacturing companies, as they have more assets (and liabilities) to reorganize during the bankruptcy trial. Finally, we add to the existing literature by providing an instrument testing the causal impact of duration using judge-specific effects to calibrate and validate our OLS estimates. The policy implication of our paper revolves around the discussion that the duration of Chapter 11 cases can be a useful indicator of its effectiveness. Indeed, Chapter 11 has been under criticism and people are trying to ascertain whether or not it is a useful way to help companies emerge from bankruptcy or if it is only dragging the bankruptcy process further out and expanding the costs associated with it.

This paper is organised as follows. Section 1 was the introduction, giving us insights and knowledge about the subject at hand. Section 2 is the literature review, deepening the understanding of what is at stake and presenting the data that is used to generate our models in detail, including the methodology used and the main variables of interests. Section 3 analyzes what impacts duration during a bankruptcy trial and defines it. Section 4 discusses the link between duration and the success of a bankruptcy trial by applying both OLS and logistic regressions. Section 5 establishes the relationship between duration and the post-bankruptcy performance of companies that had a successful trial by using predictive failure models. Finally, Section 6 provides a novel instrument to test the causal impact of duration using judge-specific effect and basing our model on the heterogeneity in the allocation of cases to judges. Section 7 concludes while Section 8 presents our results and tables.

II. Literature review

A. Chapter 11.

Chapter 11 has been an important subject of interest in the literature surrounding bankruptcy in the United States of America. Several authors have discussed its effectiveness and the debate mostly revolves around the costs associated with it. Weiss (1990) argues that the costs associated with a bankruptcy reduces the share available for redistribution around creditors and that the longer a company lasts in a bankruptcy trial, the higher these costs become. Therefore, we can understand that the duration of a bankruptcy trial is an important and complex variable to examine in order to understand the effectiveness of said trial.

Under a Chapter 11 filing, the debtor is given the chance to reorganize its assets, debts and business affairs. The main difference with Chapter 7 is that there rarely is a trustee appointed, which means that the debtor remains in possession of the business, hence the calling "debtor-in-possession". This allows the debtor to have a higher leverage when it comes to bargaining with the creditors relating to their claims and the negotiation of a plan of repayment that could satisfy both entities at once. Consequently, Chapter 11 has three main goals: paying off or reducing the debts and liabilities to a sustainable level, liquidating all the assets of a company or reorganizing into a healthier structure or entity.

Chapter 11 can be filed voluntarily or involuntary. In the former case, the debtor presents itself in front of the court to rearrange its debts and liabilities when it is nearing or is already at bankruptcy while, in the latter case, a certain number of creditors have to rally together and present sufficient evidence in front of the court in order to get the debtor into bankruptcy. In both cases, the company continues to operate as a going concern and there is a certain timeframe to follow. The first course of action of a Chapter 11 petition is the "automatic stay" injunction. It is coded under Section 362 of the US Bankruptcy Code and halts creditors from collection activities against the debtor during the remainder of the bankruptcy case. It is an important part of this Chapter because it alleviates a burden on the debtor's shoulders as it propels negotiation of the reorganization of assets.

Once a petition is filed, a company has 120 days to submit a plan of repayment that has to be approved by all sides before commencing the bankruptcy plan. This plan of repayment (or reorganization) has historically led to three different situations known as:

1. Free-fall: this is a situation where debtors and creditors were not able to reach an agreement before petition date. It is the most quarrelsome case as there is no negotiation that reached a positive outcome. As such, this might be the situation where Chapter 11 are longest as all sides need to reach a proper arrangement in order to facilitate and close the trial.
2. Pre-arranged/negotiated: in this situation, debtors and creditors have not completely reached a full reorganization plan but enough negotiations have been made to lay the grounds for one. Therefore, there is enough confidence in how the process will play out in order to exit Chapter 11.
3. Prepackaged: this is the most wanted and successful outcome. There, debtors and creditors have reached a full agreement concerning a plan of reorganization for the company. Therefore, prepackaged plans allow the fastening of consensus for the plan before the company even reaches the court which allows Chapter 11 to be smoother and quicker.

Based on these three distinct outcomes, it is clear that the duration of a trial is largely impacted by which option has been chosen by the company. As such, one of our first assumption is that duration of a trial and prepackaged cases are negatively related as we believe that a company that has reached a prepackaged plan of repayment before entering the court might spend less time in Chapter 11.

The previous literature surrounding the area of bankruptcy is quite extensive. Indeed, the subject has been one of high interest as it is a key financial metric for the economy. Hotchkiss, Ruback and Gilson (2000) have analyzed the usefulness of Chapter 11 negotiations through the valuation of companies. In this aspect, their paper can add to our analysis as we will be looking at the financial statement of the companies to see how the bankruptcy process has altered them. Moreover, Miller (2005) and Mooradian (1994) have both also analyzed the effectiveness of Chapter 11 by trying to acknowledge the fact that helping companies start again has been useful for the economy and to explain to what extent some companies have incurred more costs with the use of Chapter 11. As such, our paper follows their step to corroborate their findings in the usefulness of Chapter 11 in the USA but also to verify if its effectiveness is reduced by the length of the trial which, we will see later, can be linked to higher costs. Looking at the duration of a trial is an aspect that has not yet fully been examined and we think it is an important one to add in order to fully comprehend and recognize the use of Chapter 11 in the US Bankruptcy Code. Alternatively, Debbie and Song (2014) shows us how important the analysis of bankruptcy is but, while they look at Chapter 13 which is more inclined towards customers, we will be observing Chapter 11 which relates more to companies to expand our horizon of interest. Finally, Schoar (2007) has analyzed the outcomes of Chapter 11 based on judge specific differences which will be in relation to our own analysis of the duration of Chapter 11 trials based on the random allocation of cases to judges.

Most importantly, we define bankruptcy success in the same way that Lynn Lopucki and Joseph Doherty (2015) have: “ [success is where] the debtor continued in business indefinitely after disposition of the bankruptcy case, whether by plan confirmation, 363 sale, or otherwise.” This definition is applicable for all future references to the term success used in the context of a bankruptcy trial.

To conclude, the primary difference of this paper compared to the existing literature is that we are trying to provide a novel instrument to estimate the causal impact of duration on Chapter 11. As mentioned earlier, even though Chapter 11 has been quite studied, its analysis through duration and the use of an instrumental variable based on assignment of cases to judges has not yet been done. Therefore, we believe that the paper can fully add to the literature by covering this new aspect of Chapter 11.

B. Data presentation.

Our main data component for this research stems from the Bankruptcy Research Database (BRD) at UCLA, known as "UCLA-LoPucki Bankruptcy Research Database." It is one of the biggest database existing in the literature of bankruptcy comprising around 200 fields of data on more than a thousand large public company bankruptcies filed in US Bankruptcy Courts, since October 1st,1979. It compiles filings from PACER and Lexis Nexis to have as many observations as possible. More precisely, they define a public company as one having filed an Annual Report with the Securities and Exchange Commission for a year ending not less than 3 years prior to the filing of the Bankruptcy and a large company as one whose Annual Report reported assets worth $100 millions or more measured in 1980 dollars (approximately worth $287 millions in current dollars). The report in question is called the 10-K report and corresponds to a report that is required for all publicly traded companies by the Securities and Exchange Commission and which is made to capture the financial performance of these companies. Our current dataset runs until February 28th, 2021 and contains 475 variables for a total of 1184 observations.

For the duration variables, multiple ones can be used: *MonthsIn* and *lnmonthsin*. *MonthsIn* measures the number of months between the month on which the company filed for bankruptcy and the month on which the file was confirmed or dismissed. For our predictor variables, we will be using several dependent variables. The first one is *emerge* which is a binary variable that takes the value 1 if the company has emerged from bankruptcy and 0 otherwise. The other dependent variables will be discussed further in the paper, used for valuations of the firm to determine post-bankruptcy reorganization performance and relating them to duration.

Several models can be used to determine the relation in the models of interest. At first, a duration model is used to understand what impacts duration in our model before diving into the impact of duration itself. Basic OLS regressions will be made to first establish if there is any relevant relations between our variables; they will also allow us to ascertain if there is any endogeneity within our model which would lead to a need to create another variable to take it into account. Moreover, logistic regressions will also be used as we are dealing with dummy variable. Finally, the last model we will be exploring is an instrumental variable model in order to correct the endogeneity previously found.

III. Duration model: what impacts duration.

To start off our research, we would like to establish what impacts duration during Chapter 11 and what affects its exit rate. This can be done through a duration model. Duration models, also called survival analysis or hazard models allows us to model a dependent variable that represents a duration; in our case, we have both *MonthsIn* and its natural log, *lnmonthsin*. We will start by explaining the framework of duration models and follow it up with its application within our analysis.

A. Model framework.

As stated previously, duration models have a duration as a dependent variable. We need to create a variable and estimate its probability in order to implement it in our analysis. Therefore, let δ be the duration of the period of a trial with distribution $g(\delta)$. From here, we can define the conditional probability that a trial ends after time t as:

$$\frac{P\left\lfloor \delta\epsilon(t, t+\frac{dt}{d} \geq t)\right\rfloor}{dt} = \frac{G(t+dt) - G(t)}{dt[1-G(t)]}$$

Such that

$$\lim_{dt \to 0} \frac{G(t+dt) - G(t)}{dt[1-G(t)]} = \frac{g(t)}{1-G(t)} = \frac{g(t)}{S(t)} = h(t).$$

We define $S(t)$ as the survival function: the proportion of companies whose duration is greater than t and $h(t)$ as the hazard function or exit rate. Moreover, we have a right-censored model because, within the observations present in our dataset, we have some firms that do not emerge from Chapter 11. This model is particularly useful for us because, while taking into account whether or not a company emerges from bankruptcy, it also takes into account the number of months of the bankruptcy trial.

Right-censoring in a duration model is done through the generation of a dummy variable that we call and takes the following values: $c_i = \begin{cases} 1 \; if \; the \; company \; emerges \\ 0 \; otherwise \end{cases}$. From here, we have to use a Likelihood function to estimate our variable and find the model. The Likelihood Function is created as followed:

$$\mathcal{L}_i = [g(\delta_i)]^{c_i} * \{1 - G(\delta_i)\}^{1-c_i}$$

$$\mathcal{L}_i = [h(\delta_i)]^{c_i} * [1 - G(\delta_i)]$$

$$\mathcal{L}_i = [h(\delta_i)]^{c_i} * s(\delta_i)$$

As for the distribution used for the model, we have several ones that can be used: the exponential distribution, the Weibull distribution or even the log-logistic distribution**.** For the purpose of our research, we will follow the same distribution as Bandopadhyaya (1994) which is the Weibull distribution. The incentive for using this distribution stems from the fact that it gives the best fit for duration models compared to the other ones.

B. Application to analysis.

To create our duration model, we stipulate *MonthsIn* as the dependent variable while we defined the censored observations as the ones where the company does not emerge from bankruptcy. To understand how duration is affected in Chapter 11 we look at two different categories of covariates that relate to specific characteristics: one related to firm-specific variables and another to economy-wide variables using the same approach as Bandopadhyaya (1994). The firm-specific variable is the leverage at filing, which is the ratio of debts over assets of the company who files for bankruptcy. The economy-wide variables are the GDP for the quarter in which the case was filed and the prime rate of interest on the bankruptcy filing date. Using exactly the same model as the paper cited above, we find that our hazard function responds to the following equation: such that the coefficients estimated directly accounts for the duration dependence; if is less than 1, then there is negative duration dependence. Also it is good to note that for all of our estimates, if the coefficient has a positive impact on the hazard, then it has a negative impact on the duration.[1]

Table 1[2] presents the descriptive statistics of the different variables that are used in the model. We added a binary control variable called *prepack* which takes the value 1 if the company has reached a pre-negotiated or pre-packaged plan prior to the bankruptcy trial and 0 otherwise. As such, we can estimate several effects on duration. Table 2 presents the results of this regression. All of our estimates seem to be significant by looking at the results and we can see that the leverage at filing is both a significant predictor of financial distress but also an important factor in the chances of emergence from Chapter 11. The effect of the GDP is positive and significant which leads us to believe that there might be some link between the emergence from Chapter 11 and the overall performance of the economy. For the prime rate variable, the

[1] As denoted in Bandopadhyaya (1994) paper.
[2] All tables can be found in the Appendix section at the end

sign is negative but the effect is not significant. As explained in our introduction, Chapter 11 duration can be highly affected by whether or not a plan of repayment has been formulated prior to entering the trial. This effect can be gauged by the estimates on the coefficient of the *prepack* variable which, without surprise, has a positive sign on the hazard rate meaning that it has a negative impact on the duration. From this regression, we have a short understanding of the elements that affect duration in Chapter 11. Firm-specific as well as economy-wide variables tend to have an impact on both the probability of exit from Chapter 11 and on the duration itself. Now, we will analyze the link between duration and emergence more specifically.

IV. The link between duration and emergence

A. Descriptive statistics and first analysis.

To reiterate our research subject, we are trying to establish a link between the duration of a bankruptcy trial and its impact on the success of the trial, while taking into consideration if it is linked to an improvement in the post-bankruptcy performance of the company. The descriptive statistics of the variable *MonthsIn* can be found in Table 1. We find that the mean of bankruptcy trials is around 16.17 months, or a little over 1 year while the median is a little bit below, at around 11.43 months. Therefore, we will be analyzing our dataset within two separate groups: one composed of companies that emerged from bankruptcies in a timeframe above the mean and another one with a timeframe below the mean. This will allow us to look at the impact of duration separately to verify if the length has an impact on the success of a trial. We use the mean for simplicity purposes. From the preliminary tests, we see that there are 743 cases that took less than the mean number of days to exit Chapter 11 while 441 were longer than the mean. Table 3 gives us the correlation between *emerge* and *MonthsIn*. This table validates the assumption we had made, confirming the fact that there is less need to stay in

Chapter 11 when a plan of repayment has already been decided. Moreover, we can see that this correlation is significant at the 5% level.

The first model we would like to test is a basic regression test establishing a link between exiting Chapter 11 and the time spent in it. Therefore, we run a simple OLS regression which evaluates the following relationship: $y = \alpha + \beta X_i + \varepsilon$. In this case, the y corresponds to our dependent variable, *emerge*, which is a binary variable that takes the form 1 if a company successfully emerges from Chapter 11 as per our previous definition of success and 0 otherwise. Table 4 shows us the result from this regression: we observe that duration has a negative effect on the success of a trial. Once again, this confirms our hypothesis that duration and success are negatively correlated which follows the same spirit as the previous literature on the topic. As a matter of fact, we can assess that the coefficient on *MonthsIn* tells us that by adding one more month in the duration of the trial, the success of a trial decreases by 0.4%. To infer whether or not our results are relevant, we look at the p-value. The p-value of a variable indicates whether it is a meaningful addition to our model; the null hypothesis tests whether the response variable has any effect on our predictor variable. If the p-value is inferior or equal to 0.05, then we can reject the null hypothesis such that changes in the predictor's value are related to changes in the response variable. In our case, the p-value is equal to 0 such that we can reject the null-hypothesis. Therefore, from this model, we are able to conclude that our estimator is significant and that duration of a trial is negatively related to its success.

However, limiting our analysis to a univariate model would be too simple. Indeed, literature has shown that, while duration may be an important factor in the success of a trial, it is not the only one and caution should be applied when analyses are being made. Moreover, we can see that the is only 2% which leaves us thinking that there is more to this model than meets the eyes. We are not yet looking at the causal impact of duration and here it is more of a prediction task which is why we believe that there might be more to this model. As such, we incorporate one more variable in our next model that we think can add more power to the analysis. Furthermore, we might be able to see the omitted variable bias that might potentially be biasing the coefficient. Aforesaid, we assumed that having a prepackaged plan of repayment prior to entering court can positively affect the outcome of the trial and even speed up its process. Table 5 enables us to look at the correlations between all our variables of interest. We see that *prepack* and *MonthsIn* are negatively correlated which follows the logic of having to spend less time in trial if a plan of repayment has already been decided while *prepack* and *emerge* are positively correlated since having a prepackaged plan of repayment the probability of a successful bankruptcy trial. Constructing our model exactly like we did for the previous one, Table 5 shows us the results of the regression. We see that the effect of duration is close to being the same one as the previous regression and the effect of *prepack* is positive as expected. As it turns out, having a prepackaged plan of repayment before entering court increases the chances of success by 23.8%. Once again, we look at the p-values to determine whether these results are really relevant and we can conduct the same conclusion as the previous one because both our p-values are inferior or equal to 0.05. Here, we can infer that there is a strong relationship between having a prepackaged plan and the success of a trial; however, our question is to dissect the impact of the duration itself. Therefore, as mentioned in the beginning, we are going to make an analysis based on two subsets of the data.

The first regression will be made for cases that took less than the mean number of days and the second one for cases that took longer than it. Table 7 shows us the results of the first regression. Here, the effect of duration is very clear. The negative relation is still present but we can see that there is a bigger impact on the success of a trial. Indeed, we can see that adding a month to the duration of a trial decreases the chance of success by 1.6%. When it comes to the effect of the variable *prepack*, we can see that nothing has changed as it is still very helpful to have prepackaged plan of repayment before entering court in order to guarantee the success of a trial. Moreover, just like our previous models, the results are significant as validated by the p-values. Consequently, we move to the second regression whose results are given in Table 8. Our first reaction is to be surprised by the results as none of our independent variables seem to have any explanatory power on our predictor. However, looking back on the previous assumptions that we made, we can infer that if a case is already longer than the mean duration then there is nothing much our variables would be able to explain. We then conclude that these models validate our primary assumption that duration is negatively related to the success of a trial.

Before jumping into our next model, we would like to clarify something. Our dependent variable *emerge* is a binary variable such that it violates the assumption of normal distribution that is necessary for the linear regression model to conceptually hold. As a matter of fact, it is based on the assumption that the outcome is continuous such that the errors are normally distributed. However, the consistency of the variance of residual errors has been mitigated in our models through the use of robust standard errors. Moreover, the normality assumption can be respected through the use of the central limit theorem that states that if the sample size is not small then we can infer that, in repeated samples, the regression estimates are normally distributed. Nonetheless, we are going to be using the logit function to estimate the predicted probability of success between 0 and 1. As such, our next subsection focuses on the logistic regression and the models we can deduct from it. Moreover, by using OLS with a dichotomous variable, we want to add the fact that the interpretation of the estimators can also be read in the following way: they represent the impact of the variation of months on the probability that a company emerges from bankruptcy.

B. The logistic function.

As explained, our independent variable *emerge* is a simple dichotomous variable that only takes the values 0 or 1. In order to properly estimate the limited dependent variable model, we are going to use the following approach: we are going to choose a probability distribution appropriate for the dependent variable and then we are going to model a parameter of this distribution according to the desired explanatory variables. As a reminder, our explanatory variables are *MonthsIn*, the duration variable and *prepack*. Just like the duration model, we will begin by explaining the framework and then applying it to our analysis.

i. Model framework.

The Bernouilli distribution is a discrete probability distribution of a random variable which takes a binary output. Thus, we assume that y[3] takes the following probabilities:

$$P(y = 1) = p$$

$$P(y = 0) = 1 - p$$

From which it is easy to establish the following facts: $E(y_i) = p$ and $V(y_i) = p(1 - p)$. Following these findings we make the following proposition.

Proposition 1: The estimator for the parameter p using Maximum Likelihood is

$$\hat{p}_{MV} = \frac{1}{N}\sum_{i=1}^{N} y_i = \bar{y}.$$

However, it is necessary to parametrize $p = f(X_i)$ in order to incorporate a vector of explanatory variables X_i of dimensions $1 \times K$. Based on how we have restricted our parameters where $p \in [0,1]$ and $X_i \in R^K$, we can see that we need to impose two restrictions in our model such that $f(.): R^K \to [0,1]$. One way to properly impose these two restrictions is to use the logistic function. If we define $F(.) = \Lambda(.)$ as the logistic function and $g(X_i, \beta) = X_i\beta$ then we can obtain our logit model such that

[3] As of here, y refers to the variable *emerge*, our dependent variable.

$$f(X_i) = \Lambda(X_i\beta)$$

where our function $\Lambda(.)$ can be written as

$$\Lambda(.) = \frac{1}{1 + e^{-z}} = \frac{e^z}{1 + e^z}.$$

Therefore, this model will model the conditional probability of our dependent variable Y=1 given our independent variables X_i or the same thing but for Y=0.

Now that the framework has been set, we will be moving to the application of this model in our analysis.

ii. Application to analysis.

We use logistic regressions in the same way that we had in our OLS regression models. Table 9 gives us the results of said regression. The chi-square equals 69.01 and the p-value of the model is equal to 0 which indicates that the model fits significantly better than a model with no predictors. Therefore, we can say that both our independent variables are useful and relevant in explaining our dependent variable. If we look at individual variable coefficients we can see that for a one unit increase in *MonthsIn*, the log odds of success in a bankruptcy trial decrease by 0.01 and a one unit change in *prepack* increases the log odds of success by 1.97. Another way to analyze the outcomes of this regression is to look at the odds ratio. They give us multiplicative effects on the odds rather than simple additive effects. The results are shown in the table next to Table 9 for simplicity. We note that odds that are between 0 and 1 are considered to have a negative effect because they decrease the odds while the ones above 1 have a positive effect (since multiplying them will increase the odds). Consequently, we see that the odds of success of a bankruptcy trial are predicted to decrease by 0.99 for each additional month spent in a trial while they are predicted to grow by 7.2 for each time there is a prepackaged plan of repayment. As such, the logistic regression has enhanced the first findings we had in the OLS regression, corroborating the fact that duration of a trial and success are negatively related. Our findings are similar to the ones that previous literature had shed light on. Indeed, Bris, Welch and Zhu (2006) found that time spent in a bankruptcy trial serves as a good proxy for indirect bankruptcy costs inferring that a longer trial might imply higher bankruptcy costs. As a consequence, the amount of bankruptcy costs becomes so high that it hinders the capacity of the company to emerge back from bankruptcy as there might not be enough money left to properly recalibrate the existing company. However, we want to see how duration has also affected the companies who were able to successfully emerge from bankruptcy. In the next section, we will analyze the impact of duration on the post-bankruptcy performance of these companies.

V. Duration and post-bankruptcy performance

A. What is at stake.

Now that we have established a link between duration of a trial and its related success, we can now dive into the second part of our research subject. As a matter of fact, the question of interest is to test whether there is a link between the length of a trial and the post-bankruptcy performance of a company. Through their extensive research, the "UCLA-LoPucki Bankruptcy Research Database" was able to document some financial measures from company that emerged from bankruptcy if they filed a new 10-K report in the same year or in the year following their emergence. This particular question has been at the center of the existence of Chapter 11 as several authors have tried to question its effectiveness in helping companies delay or avoid their liquidation. Indeed, the costs associated with Chapter 11 and the fact that some companies are permitted to continue as a going concern have been at the forefront of the existing literature. Authors such as Denis and Rodgers (2007) have analyzed what happens during Chapter 11 and how it relates to the outcome of the trial, specifically in the context of the viability of a company that emerges. They conclude that Chapter 11 helps promising companies re-establish themselves after they have faced financial distress and that the impact of successful reorganization is highly dependent on the operating margin. As such, we will follow their steps and analyze these links with our variables.

The first variable that we will be looking at is the change in assets. Indeed, as explained in the presentation of Chapter 11, the main goal is to reorganize the assets and liabilities of a company to help it exit its bankruptcy position. As such, it is important to relate the effect of duration to see to which degree it is helpful in the reorganization of a company. We begin by doing a basic OLS regression of the change in assets on the change in liabilities and the change in months. As we can see from Table 10, the results are not significant and, when pushing the test a bit further and analyzing whether our residuals are normal, we can see that the residuals are not normal and, thus, the interpretation and the results themselves are not to be taken into consideration. As such, we take the log of all of our variables to correct for the normality of our residuals. In Table 11, the results of the new regressions are shown and this time they are relevant. Moreover, the model has a very high R^2 meaning that the model is very well fitted at approximately 75.8%. Table 12 and 13 compare how the residuals are fitted to normality and we can assess that taking the natural logarithms of our variables has enabled us to enforce normality of the residuals and help us trust our inferences. Based on this new regression, we can infer that a one percent increase in the number of months decreases the assets of the company by 0.06% ceteris paribus. Once again, this is in alignment with our assumptions, as increasing the duration of a trial might be in association with an increase in the bankruptcy costs which would lower the available assets of a company. To reiterate, a lengthy reorganization process implies more discussion and negotiations between all classes of creditors and the debtors which is usually costlier.

The second variable that we will be using to evaluate the performance of a company after they emerged from bankruptcy is *BondPriceMoveDuring* which details the movement of the Bond Price during the trial. OLS regressions can be used to estimate the links between our variables as the dependent variable is not dichotomous and we can rest assured that the assumptions of the linear model have been respected. The results of the regression are shown in Table 14: we see that duration here has a positive effect on the price of a bond and we can infer that adding one month in the length of a trial increases the price of a bond by 57%. The p-value of the regression seems to imply that our variable is statistically significant. However, we would like to test for endogeneity in order to verify if our model is well-fitted and properly defined. Table 15 draws the residual plot of the regression, fitting the values over the red line. As we can observe, the points are really concentrated on the left-side of the graph but there are a lot of outliers that we see in the graph. Indeed, in order to eliminate the probability of endogeneity, we usually expect the graph to resemble what we call a "bird nest" where all the points are regrouped in one central group. It is almost the case for our model but we can see that the presence of that many outliers calls for some doubt in the existence of endogeneity in the model. Endogeneity stems from the following misspecifications in the model: omitted variable bias, simultaneity, functional form misspecification and/or selection bias. In order to correct for this problem and assess the causal impact of duration in our model, we will be creating an instrumental variable to enhance the model. This variable will be discussed further in the paper.

Finally, another way to estimate post-reorganization performance of a company is to look at the emerging EBITDA. The EBITDA corresponds to the Earnings Before Interests Depreciation and Amortization. This financial metric is used as a proxy to estimate a company's cash flows which, in the context of a bankruptcy, can help us understand and assess the liquidity of the company. Unfortunately, our dataset is highly reduced when it comes to this variable as it has been difficult to estimate it properly, leaving us with only 358 observations. However, the links can still be established as Table 16 shows us. Here, we have a positive relationship between duration and the emerging EBITDA. Indeed, we can interpret that if we add a month to the duration of a trial then the EBITDA grows by 341%. This is a rather surprising finding compared to the one we had with the first variable that we analyzed; we had predicted that increasing duration has a negative impact on the assets and liabilities. However, EBITDA does not include depreciation in its calculations and can lead to distortions when it comes to the inclusion of fixed assets. As such, EBITDA and assets might be inversely related in certain companies that have a high volume of assets in their balance sheet, such that the results of our findings become clear. Nonetheless, the R^2 of that equation itself is quite small which leads us to believe that the link between duration and EBITDA cannot be properly made and is not the right direction to look at when analyzing duration and post-bankruptcy performance of a company. This follows the logic we explained earlier where we were trying to model a prediction task.

We have assessed a part of the impact of duration on the post-bankruptcy performance of companies. However, another very interesting way to look at the performance of companies that go bankrupt is to calculate the Altman's Z-score. The next two sub-sections will be dedicated to explaining the model and applying it to our analysis. This first part is just to look at a basic analysis of duration on post-performance for companies who had a successful bankruptcy trial. The logic behind the use of the Altman's Z-score is to look at the different financial metrics that make up a company's financial statements and to see which ones have been mostly affected by the duration of the trial.

B. Altman's Z-score model.

Altman's Z-score model has been constructed with the intended purpose of discerning financial distress in companies. Created in the 1960s, this model has been reviewed by several researchers to assess its effectiveness in predicting bankruptcy. Grice and Ingram (2001) conclude that the model is a useful one for this type of research. Certainly, failure prediction models such as this one are of high interest to the financial sectors as it poses two distinct benefits: on the one hand, it might lead to a new source of income where people can start short selling some of the assets they believe will go bankrupt and, on the other hand, it helps companies and officials verify if they need to review their financial strategies in order to meet both short and long-term liquidity needs.

The model is based on what can be described as a "credit-strength test that gauges a publicly-traded manufacturing company's likelihood of bankruptcy."[4] The model is based on the distinction between manufacturing and non-manufacturing companies and the effect is observed following these two formulas:

$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0X5$ for manufacturing firms

$Z = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4$ for non-manufacturing firms[5]

Where

$$X1 = working\ capital/total\ assets$$

$$X2 = total\ liabilities/total\ assets$$

$$X3 = EBIT/total\ assets$$

$$X4 = value\ of\ equity/total\ liabilities$$

$$X5 = sales/total\ assets$$

These different ratios represent important financial ratios companies use to determine their financial strength. X1 is a liquidity ratio showing the ability of a company to convert their assets to cash. X2 is a leverage ratio which assesses the total capital of the firm by dividing which part of it originates from debt: it shows how much the firm relies on debt to finance their activities. X3 is a profitability ratio which determines how well a company uses its assets to generate revenues and offer profits to its shareholders. X4 is a solvency ratio which shows us the capacity of the firm to meet its short-term liquidity obligations. Finally, X5 is the activity ratio that

[4] Definition used by financial sources.
[5] This equation is taken from Min Xu's 3 Essays on Chapter 11 Bankruptcy

resembles the profitability ratio to the difference that it assesses the ability of a company to efficiently use their assets to convert them into sales. Most of these values were readily available in our dataset, for the exception of the following variables:

1. Working Capital: we calculate this variable as assets minus liabilities, reported in the 10-K report.
2. Equity: this variable was offered by the UCLA-LoPucki Bankruptcy Research Database and is calculated as $(assets - liabilities)/assets$.
3. Accordingly, both these variables have been calculated for the period before and after filing for bankruptcy, when the 10-K report was available to us.

To properly ascertain the relationship between performance and relating it to the subject at hand, we will be calculating both the Z-score prior to filing for bankruptcy to the one after emerging back from bankruptcy. As such, we hope to be able to decipher an explanation on the impact and effectiveness of Chapter 11 and analyzing which ratios have been improved in order to have a better score that allows the company to emerge and might prevent it from refiling for bankruptcy. Moreover, we will examine this topic in the context of duration to see if the length of a trial has any impact on the improvement of said ratios and to what extent does it explain the emergence of the companies.

C. Judging post-bankruptcy performance through a sector-based analysis.

Now that we have laid the ground for our model, we will now implement it in our dataset. Our dataset has been significantly reduced. As a matter of fact, we only have accurate data for 304 firms and these will be our companies of interests. To make the difference between the two types of firm, we create a binary variable named *manufacturing* which takes the value 1 if the company is a manufacturing one and 0 otherwise. Out of these firms, 105 are classified as manufacturing firms per the SIC Code while 199 are coded as non-manufacturing. Table 17 gives us a financial outlook of all firms pre-and-post Chapter 11. As such, we are able to see improvements in key areas of the financial statement. Indeed, there is a real improvement in the Working Capital post-bankruptcy filing which is consistent with the idea that a successful bankruptcy trial is one where a company is able to significantly reduce its debt to a sustainable level. We recall that Working Capital is calculated as the subtraction of assets and liabilities and we can observe that the median of Working Capital goes from 15.91 million to 135.30 million which is an improvement of 750%. Naturally, we also observe that liabilities go from a median of 934.21 million to 463.69, declining by a little more than 50%. Consequently, despite critics disputing the effectiveness of Chapter 11, we can assess from our dataset that the Chapter has successfully allowed these companies to reconstruct themselves and diminish the burden of their liabilities that might have brought them to bankruptcy.

In order to establish the sector-based analysis, it is also crucial to look at the difference in financial statements between manufacturing and non-manufacturing firms. Therefore, we will decompose our descriptive statistics between both manufacturing and non-manufacturing firms. Table 18 shows us the results for manufacturing firms while Table 19 is for non-manufacturing firms. For both types of firms, we can establish that there is a real improvement in all aspects of the financial statements. Indeed, looking at the liabilities in particular, we see that manufacturing firms have had their level decrease by 47.1% while non-manufacturing firms have decreased by 53%, basing our results around the median. Basing our observations around the median helps us limit the impact of outliers. Nonetheless, there seems to be a higher impact on non-manufacturing firms in the context of reorganization of their assets and liabilities. Other values of improvements are available in both Tables. Now that the financial outlook of both types of companies have been studied, we will now move to the observation of the Z-score.

Across all firms, we can see that there is an improvement in the Z-score. Indeed, the mean of Z-score goes from 2.48 to 3.51 after emerging. As per Altman's theory, we consider a firm to be in the safety zone if their Z-score is above 3 and 2.6 for manufacturing and non-manufacturing firms respectively. Keeping this in mind and looking at Table 20, we could comment that both types of firms are now in the safety zone after they have emerged from bankruptcy. However, is the effect really the same for manufacturing and non-manufacturing firms or is one type of firm dominating the other? To answer our question, we dissect the Z-score between the two types of firms and the disparity then becomes clear. Table 20 also gives us the before and after of Z-score for both manufacturing and non-manufacturing firms: we observe that non-manufacturing firms seem to be pushing our results upwards as the improvement in Z-score is mostly from their side: more specifically, *ZscoreB* is the Z-score prior to filing for bankruptcy while *ZscoreA* is the Z-score after emergence from bankruptcy. The mean of Z-score for manufacturing firms goes from 2.63 to 2.71 whereas the one for non-manufacturing firms goes from 2.4 to 3.93 showing an improvement of 63.75% for non-manufacturing compared to 3% for manufacturing. Moreover, we see that manufacturing firms do not reach the safety level after emerging back from bankruptcy which could potentially lead to refiling for bankruptcy in the following years.

But what is the effect of duration on these values? As mentioned before, we want to understand if duration has an impact on the valuation of these firms which we measure using the Z-score. Since the Z-score is made up of several financial ratios which estimate different financial aspects of the company such as liquidity, leverage, profitability, solvency and activity, we can use it as a proxy for measuring the valuation of a company post Chapter 11. Across all firms, the number of Months spent in Chapter 11 varies by a lot going from 0.6 month to 131 months, as shown in Table 21. The mean is situated at 15.36 months, which places us around a year and a half while the median is significantly below at 9 months, or a full trimester before the end of a year. However, the duration is largely pushed by manufacturing firms whose mean is around 20 months while the non-manufacturing firms mean is at 12.76 months, shown in

Table 21. Once again, the median is significantly smaller than the mean at 13.3 months for manufacturing firms and 8.87 months for non-manufacturing. This disparity in timeframe might be explained by the complexity of the structure of manufacturing firms. Indeed, we can assume that they might be larger in size but also that they might have more assets and liabilities to restructure given the fact that they have more materials, work inventories and such to take into account during the bankruptcy trial. Moreover, we might be inclined to imply that the fact that there are more non-manufacturing firms that survived bankruptcy is a direct link of that size. As a matter of fact, bigger companies tend to incur more costs during the bankruptcy process which, as discussed previously, can also be assessed by the length of a trial. Therefore, in this case scenario, duration is best analyzed as a proxy to indirect bankruptcy costs.

However, is it really true that duration only implies higher costs and, thus, a lower chance of emerging from bankruptcy or are these effects mitigated? Advocates of Chapter 11 have been campaigning on the basis that a longer trial might also imply a better renegotiation of assets and liabilities of the firm. Therefore, they state that a company that stays longer in a bankruptcy trial might have a higher chance of increasing their profitability once they emerge from bankruptcy. To evaluate their point, we take a closer look at our profitability ratio that we calculated for Altman's Z-score. Table 22 allows us to look at the correlation between the profitability ratio post-bankruptcy *X33* and the length of a trial. As we can see, the two are positively correlated and this relationship is significant at the 5% level. Therefore, we start a simple regression to see if duration is a relevant variable in the improvement of the profitability ratios. As Table 23 demonstrates, there is a positive relationship between our two variables where adding 1 month in the duration of a trial increases the profitability ratio by 0.2%. However, we note that the strength of this relationship is pretty low and, thus; we can assess that the effect of duration on the improvement of the profitability ratio might be mitigated by other variables that are not present in our model. Dividing the analysis between manufacturing and non-manufacturing firms, we observe that the effect is the same for both types of firms as shown by Table 24 and 25. They both display positive relationships among the profitability ratio and the duration of a firm; nonetheless, the effect is still very small, shown by the small coefficients.

As a conclusion, the sector-based analysis is a good one to use to decipher the relevance of duration on Chapter 11 bankruptcy and on the post-bankruptcy performance of a company. As we were able to understand, the effect of duration is quite mitigated and it is important to keep in mind that duration might not be the best angle to analyze the effectiveness of Chapter 11. However, we have noted previously that our models might have endogeneity in them which leads us to our final model with the creation of an Instrumental Variable to correct them and assess the integrity of our analyses.

VI. The causal impact of duration through judge-specific differences

To conclude our research, our last approach is through the use of Instrumental Variable regression. As discussed before, some of our estimates might not be fully specified as they suffer from omitted variable bias. Indeed, our models are quite restricted in the choices of variables made but also because there might be some correlations that are not seen within the error term, rendering our analyses inconsistent or incomplete. In the words of Schoar and Chang (2008), "*testing the causal impact of specific aspects of the bankruptcy process on the efficiency of bankruptcy resolutions constitutes a difficult empirical challenge since the ruling themselves are endogenous to the outcome of the case. A simple cross-sectional test of judge decision on case outcomes does not allow us to assess the causal impact of particular rulings in Chapter 11 since the motions a judge approves are endogenous to the particular of the case.*"

Furthermore, our paper intends to add to the existing literature surrounding Chapter 11 by deepening the understanding of the effect that duration plays on it. As a consequence, we provide a novel instrument to estimate the causal impact of duration in the current Chapter 11. To identify the causal effect of duration on trial outcome and post-bankruptcy performance, we rely on judge heterogeneity in case allocation. As a matter of fact, if we are able to prove that judges are randomly assigned to each case then we will be able to create an instrumental variable based on the idea that the effect of duration might be affected by the judge itself and not the particular of the case. Previous literature has supported our point of view and has concluded that judge-specific effects are quite prominent and responsible for the variations in the decisions taken during Chapter 11 (such as conversion to Chapter 7 or the granting or denying of certain motions). Consequently, if there is no significant difference in the set of cases assigned to each judge, then we will be able to interpret the difference in the duration of rulings and its impact on the post-performance of the firm as the result of the judge-specific effect. However, it is important to note that this paper will only cover the judge-specific effect in the context of duration and not in any other aspect that might have been covered in previous research papers. For further discussion on the impact of judge specific difference, please refer to Bernstein, Colonnelli and Iverson (2018). This section will be divided into two parts: we first prove that cases are randomly allocated to judges and we follow it by applying the instrumental variable regression in our analysis.

A. Proof of random allocation of cases to judges.

Our first angle to tackle is to prove that there is random allocation of cases to judges. The importance of it relies on the idea that the instrument we will be creating will respect the primary conditions needed for an instrument to be recognized as such. These conditions will be discussed during the creation of the instrument. We theorize that the allocation of cases to judges has to be independent of judges' choice or time and also firm characteristics. Indeed, we want to prove that cases are not given to a specific judge because of the characteristics of the firm that is filing for bankruptcy. Those firm-specific characteristics regard the size of assets prior to bankruptcy, the number of employees which can be viewed as a proxy for the size of the firm, the return on assets prior to bankruptcy and the leverage at filing. All these variables will be defined and labeled in our dataset and explained throughout the paper such that they maintain relevancy. At a first glance, random allocation of cases to judges seems pretty self-explanatory and natural when it comes to US bankruptcy courts as we know that the courts use a blind rotation system to assign cases to judges, which randomizes filers to judges within each court. However, following previous literature accounts, this paper is not advancing that there is random allocation across bankruptcy courts but mostly that there is random allocation within a given district court. The former cannot be advanced as a company is legally allowed to file for bankruptcy in one of these 4 locations per the US bankruptcy Code Title 28 Chapter 87 Paragraph 1408:

1. The debtor's principal place of business
2. The location of the debtor's principal assets
3. The debtor's place of residence, usually where it is incorporated
4. Any district where an existing bankruptcy case is pending against any of the debtor's affiliate

Research has shown that there might be a tendency for companies to file within the Delaware and New York City district, both because Delaware has implemented lax rules when it comes to business incorporation but also because New York has the highest number of cases which could imply that they have the highest number of experienced judges. As such, this can lead to what is known as forum shopping; however it has been widely condemned by previous literature such as LoPucki (1999). Therefore, we need to test whether the random allocation of cases to judges holds in our dataset. We recall that our dataset comprises the filings of large companies in the US since 1979 and the existing literature establishing the random allocation of cases to judges has mostly been focused on small business filings. Nonetheless, Iverson, Madsen, Wang and Xu (2018) have implemented the research to large companies and following in their steps, we focus our proof on the link between the firm characteristics and the choice of a specific judge.

In order to avoid missing any observations, we refer ourselves to the period post "Privacy Cut-off" which, as defined by the "UCLA-LoPucki Bankruptcy Research Database" concerns any cases before 2003. This drops the number of cases to 568 with 128 unique judges. With such a high number of judges, it is only natural to see that there is a difference in their propensity of duration, but we keep in mind that this difference is also affected by the number of cases the judge has overseen during our period. Among these 128 judges, there are 12 who accumulate more than 10 cases individually as shown by Table 30 which we use as the cut-off number of cases to characterize a judge as experienced. Table 26 shows us the descriptive statistics of duration across our period and by judge. We pool together all the judges who have been assigned less than 10 cases during our study period and individualize each judge who has more than 10 cases. This entails that all judges with less than 10 cases are under a single dummy variable.

To reiterate our previous point, we need to verify that firm characteristics have no impact on the decision of having a specific judge oversee a case. As discussed before, we base our analysis on the following firm characteristics prior to filing: the size of assets, the number of employees, the return on assets (defined as net income divided by assets) and the leverage (defined as liabilities divided by assets). Table 27 divulges the descriptive statistics of every firm in our dataset for these characteristics. To be certain of our results and dissipate any doubt on the possibility of hidden interaction that could lead to statistically significant estimates, we run a regression with *judge* as the dependent variable over all the different firm characteristics at once. If we find that the coefficients are not statistically significant then it is a good sign for us that cases are randomly allocated to judges. Once we can hypothesize this, we will be able to discuss the creation of the instrument to be used in the final regressions. Since our variable *judge* is a categorical dependent variable, we have to use the multinomial logit model to run our regression in order to estimate it. We use the first category, the one where we put all judges with less than 10 individual cases together, as the base one and run our regression to evaluate our estimates. We also add *involuntary* as a binary control variable to determine whether or not having the bankruptcy filed involuntarily or not affects the choice of the judge. After conducting the regression, we realize that the coefficients are not significant in any of the results**.** To confirm our findings, we run an F-test on the coefficients where the null hypothesis is the following:

$$H_0 = all\ of\ the\ regression\ coefficients\ are\ equal\ to\ zero.$$

We find that the p-value of the test is 0.4374 such that we are unable to reject the null hypothesis. Therefore, we are able to conclude that cases are randomly allocated to judges because we can see that it is not dependent on the firm characteristics.

B. Instrument creation and analysis.

Now that we have proved that cases are randomly allocated to judges, we are able to fully create an instrument which will respect the necessary conditions. So far, we have run basic OLS regressions following the model $y = \beta X_i + u$ where we try to estimate the effect of duration on several dependent variables such as whether it affected the probability of emergence or the post-bankruptcy performance of the firm. However, duration might be linked to some unobservable characteristics contained in the error term such that there exists a violation of the zero conditional mean assumption where $E(u/X) = 0$. As such, we need to create an instrument that follows these 3 conditions:

1. It must exhibit strong and meaningful correlations with X
2. It must satisfy the orthogonality conditions such that $E(uZ) = 0$

3. It must be properly excluded from the model such that the effect on the response variable is indirect.

Now that we know the conditions necessary to create an instrument, we can move to its creation. A useful instrument that has been commonly used in the field is a standard leave-one-out measure where we compute the mean duration of all cases for each judges but the i-th case. Bernstein (2018) explains that the use of a leave-one-out measure *"deals with the mechanical relationship that would otherwise exist between the instrument and the duration for a given case."* As such, we conjecture that a leave-one-out measure will be useful in our case to distinguish the effect of duration. Therefore, we first look at the sum of months spent in Chapter 11 across judges and across all years within our period. Then, we compute the duration of all the cases per judge excluding the case we are looking at to plant the base for the leave-one-out mean. Afterwards, we count the number of cases given to each judge over our period of interest like Table 26 has shown us previously. Using these two variables, we combine them together and divide the total duration excluding the previous case over the number of cases minus 1. Putting a mathematical model in action, our instrument is based on the following equation:

$$instrument1_{ij} = \frac{1}{n_{ij} - 1} \sum_{i \in (j), i \neq i'} y_i$$

Where $i \in (j)$ means that case i is judged by judge j and $i \neq i'$ implies that we are not taking into consideration the case observed. As mentioned, we subtract the number of cases overseen by each judge by 1 in order to take into account the exclusion of the current case. y_i represents the outcome of the case analyzed which for our purpose, represents the time spent in Chapter 11 counted in Months. Table 29 and 30 show us both the correlation between the instrument and our variable *MonthsIn* as well as the descriptive statistics for both. As we can see, the correlation between the two variables is significant at the 5% level which validates what we need to fulfill our conditions of a good instrument.

Now that our instrument is created, we move onto applying it into our model to assess the impact of duration that we had previously calculated. We want to look at the logarithmic variables like we had done in the post-bankruptcy performance part and see if the effect of duration still holds with our instrument. Table 31 performs an instrumental variable regression using first and second stage analysis to look at the relationship between the duration of a trial and the size of assets and liabilities prior to filing for bankruptcy. We instrument the duration variable *lnmonthsin* by using the instrument we created. The table gives us the estimates from the regression and we can see that, as conjectured, the duration of a trial has a negative relationship with the size of assets (even taking the judge-specific effect into consideration) which validates our train of thought. To make sure that our estimates are consistent and respect the conditions needed, we perform 2 more tests to validate it. The first one is an under-identification test using the Anderson Cannon. Corr. LM statistic and its following p-value. Since the p-value is significant in our model, we can reject the null hypothesis that states that the model is under-identified. Following this, we perform a strength test using the Cragg-Donald Wald F-statistic compared to the widely known Stock-Yogo measure; in our case, the F-statistic is always superior to the Stock-Yogo values, implying that our instrument is not weak. Indeed, this test is made to see if the instrument properly identifies the variable of interest and if it fully defines et replaces our variable and its replicates its explanatory power. Therefore, we can be sure that our instrument holds in this dataset. We follow up our use of the instrument by testing it a bit more directly and putting it into equations with other variables to estimate its direct effect. Based on our first few models, we reapply a logistic regression on the probability of emergence from a bankruptcy trial and estimate whether the effect of duration is still the same. Using the reduced form estimation will help us verify whether or not the sign still holds with the instrument. As Table 32 demonstrates, we see that duration keeps the same effect, especially by the negative sign in front of the coefficient and we can still see that duration of a bankruptcy trial and the chances of emerging back from bankruptcy are negatively related. Finally, to estimate the impact of duration on the post-performance of a company we will be looking at the change in EBIT of the company. Different from EBITDA, EBIT represents the Earnings Before Interest and Taxes and is also a measure of profitability of the company. As we can see in Table 33, duration has a negative impact on the change in EBIT such that a one percent change in the number of months would decrease the EBIT by 2.2%. Once again, we are using the reduced form estimates in this equation. This is consistent with the fact that we had previously seen a negative relationship between the change in assets and the duration of a trial. Unlike EBITDA that we had analyzed before, EBIT more directly takes into account the assets such that the impact of duration should bear the same sign as when we value it for assets. The change between EBIT and EBITDA is made to account for differences in signs. Indeed, as previously mentioned, EBIT takes into account the amortization of assets and we thought it would be relevant to analyze it to verify if it followed the same sign as the use of assets in prior regressions.

As a conclusion, we have provided a novel instrument here that allows us to estimate the causal effect of duration on Chapter 11 which leads us to see that duration has a negative impact on most of the outcomes of Chapter 11. This concludes our research and is validated by previous literature on the subject.

VII. CONCLUSION

Using the “UCLA-LoPucki Bankruptcy Research Database”, this paper provides evidence of the impact of duration on Chapter 11. By observing its impact on the probability of having a company emerge from bankruptcy and on the reorganization and performance of a company once it has emerged, this paper has provided significant conclusions. The first aspect follows the existing literature and comes to the conclusion that having a longer bankruptcy trial has a negative impact on the chance of emergence. Our suspicion relates to the idea that a longer trial implies higher costs and less money to become operational again. For cases where companies were able to emerge, we visited the impact of duration on their performance by looking at the values they filed in the 10-K report following their emergence. We were able to link the fact that duration also has a negative impact on the post-performance of these companies which follows the idea we submitted earlier as they might have less assets to reorganize themselves with since the bankruptcy process was long and costly. Furthermore, we look into a sector-based analysis to evaluate how duration is linked with the biggest ratios used to evaluate a company and to see if there is a difference between manufacturing and non-manufacturing firms, in order to judge whether firm-specific effects had any relevancy in our analysis. It shows that firm-specific effects might be important since the size of a specific company might also be the reason why they tend to stay longer in a trial. Finally, we provide a novel instrument to exogenously estimate the impact of duration using the random allocation of cases and to see whether judge-specific effects would give us a better explanation. Using the leave-one-out measure, we were able to validate and formalize our previous results. To reiterate, the policy implication of our paper revolves around the discussion that the duration of Chapter 11 cases can be a useful indicator of its effectiveness.

As mentioned, it is worth noting that our paper does not fully question the impact of judge bias on Chapter 11. Furthermore, our paper can be extended and completed by complementary research to deepen our instrument and our understanding of the impact of duration on Chapter 11.

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VIII. APPENDIX

All tables and results are presented in the following pages.

Table 1: Descriptive statistics for duration model covariates.

Variable	N	Mean	Std Dev	Min	0.25	Median	0.75	Max
MonthsIn	1167	16.17	16.83	0.30	4.93	11.43	20.83	148.93
prepack	1184	0.12	0.33	0	0	0	0	1
leverage	1165	1.03	0.53	0.06	0.78	0.94	1.14	7.57
GDP	1183	84.72	18.66	41.30	74.65	83.58	97.24	118.87
Prime rate	1184	6.10	2.75	3.25	3.50	5.25	8.25	20.00

Table 2: Duration model estimates.

Weibull PH regression

_t	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
prepack	0.883	0.369	2.39	0.017	0.159	1.606	**
gdpfiling	0.033	0.005	6.43	0.000	0.023	0.043	***
primefiling	-0.023	0.030	-0.75	0.452	-0.082	0.037	
leveragefiling	-0.728	0.173	-4.22	0.000	-1.066	-0.390	***
Constant	-7.494	0.643	-11.65	0.000	-8.755	-6.233	***
ln_p	0.391	0.036	10.99	0.000	0.322	0.461	***

Mean dependent var	16.207	SD dependent var	16.836
Number of obs	1149.000	Chi-square	124.922
Prob > chi2	0.000	Akaike crit. (AIC)	1418.204

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Table 3: Correlation between emerge and MonthsIn.

Pairwise correlations

Variables	(1)	(2)
(1) emerge	1.000	
(2) MonthsIn	-0.149*	1.000

* shows significance at the 0.05 level

Table 4: OLS regression between emerge and MonthsIn

Linear regression

emerge	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MonthsIn	-0.004	0.001	-4.74	0.000	-0.006	-0.002	***
Constant	0.767	0.018	42.64	0.000	0.731	0.802	***

Mean dependent var	0.700	SD dependent var	0.458
R-squared	0.022	Number of obs	1145.000
F-test	22.422	Prob > F	0.000
Akaike crit. (AIC)	1439.641	Bayesian crit. (BIC)	1449.728

**** p<0.01, ** p<0.05, * p<0.1*

Table 5: Correlation between prepack, emerge and daysin.

Pairwise correlations

Variables	(1)	(2)	(3)
(1) emerge	1.000		
(2) MonthsIn	-0.149*	1.000	
(3) prepack	0.204*	-0.314*	1.000

* shows significance at the 0.05 level

Table 6: OLS regression between emerge, MonthsIn and prepack.

Linear regression

emerge	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MonthsIn	-0.003	0.001	-2.84	0.005	-0.004	-0.001	***
prepack	0.238	0.028	8.53	0.000	0.184	0.293	***
Constant	0.712	0.022	33.01	0.000	0.670	0.754	***

Mean dependent var	0.700	SD dependent var	0.458
R-squared	0.049	Number of obs	1145.000
F-test	71.743	Prob > F	0.000
Akaike crit. (AIC)	1409.692	Bayesian crit. (BIC)	1424.822

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Table 7: OLS regression for cases that took below the mean timeframe.

Linear regression

emerge	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MonthsIn	-0.016	0.005	-3.53	0.000	-0.026	-0.007	***
prepack	0.144	0.040	3.59	0.000	0.065	0.224	***
Constant	0.835	0.042	19.97	0.000	0.753	0.917	***

Mean dependent var	0.745	SD dependent var	0.436
R-squared	0.073	Number of obs	725.000
F-test	54.544	Prob > F	0.000
Akaike crit. (AIC)	804.514	Bayesian crit. (BIC)	818.273

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Table 8: OLS regression for cases that took above the mean timeframe and were prepacked.

Linear regression

emerge	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MonthsIn	-0.001	0.001	-0.87	0.384	-0.004	0.001	
prepack	0.031	0.276	0.11	0.911	-0.511	0.573	
Constant	0.659	0.047	13.98	0.000	0.567	0.752	***

Mean dependent var	0.624	SD dependent var	0.485
R-squared	0.002	Number of obs	420.000
F-test	0.391	Prob > F	0.677
Akaike crit. (AIC)	588.279	Bayesian crit. (BIC)	600.400

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Table 9: Logistic regression between emerge, MonthsIn and prepack.

Logistic regression

emerge	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MonthsIn	-0.011	0.004	-2.87	0.004	-0.019	-0.004	***
prepack	1.973	0.375	5.25	0.000	1.237	2.708	***
Constant	0.892	0.099	8.98	0.000	0.698	1.087	***

Mean dependent var	0.700	SD dependent var	0.458
Pseudo r-squared	0.049	Number of obs	1145.000
Chi-square	69.078	Prob > chi2	0.000
Akaike crit. (AIC)	1334.953	Bayesian crit. (BIC)	1350.082

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Variable	Odds Ratio
MonthsIn	0.99
Prepack	7.19
Constant	2.44

Table 10: Regression between assetchange, MonthsIn and liabchange

Linear regression

assetchange	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
liabchange	0.097	0.521	0.18	0.853	-0.928	1.121	
MonthsIn	10.630	6.993	1.52	0.129	-3.121	24.380	
Constant	-756.665	582.420	-1.30	0.195	-1901.834	388.504	

Mean dependent var	-729.263	SD dependent var	5276.348
R-squared	0.008	Number of obs	383.000
F-test	1.754	Prob > F	0.174
Akaike crit. (AIC)	7654.247	Bayesian crit. (BIC)	7666.091

**** p<0.01, ** p<0.05, * p<0.1*

Table 11: Regression with log variables

Linear regression

lnchangeassets	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lnchangeliab	0.751	0.058	12.90	0.000	0.637	0.866	***
lnmonthsin	-0.066	0.018	-3.71	0.000	-0.102	-0.031	***
Constant	0.277	0.064	4.34	0.000	0.152	0.403	***

Mean dependent var	-0.556	SD dependent var	0.935
R-squared	0.758	Number of obs	383.000
F-test	89.291	Prob > F	0.000
Akaike crit. (AIC)	497.593	Bayesian crit. (BIC)	509.437

**** p<0.01, ** p<0.05, * p<0.1*

Table 12: residuals before logging variables

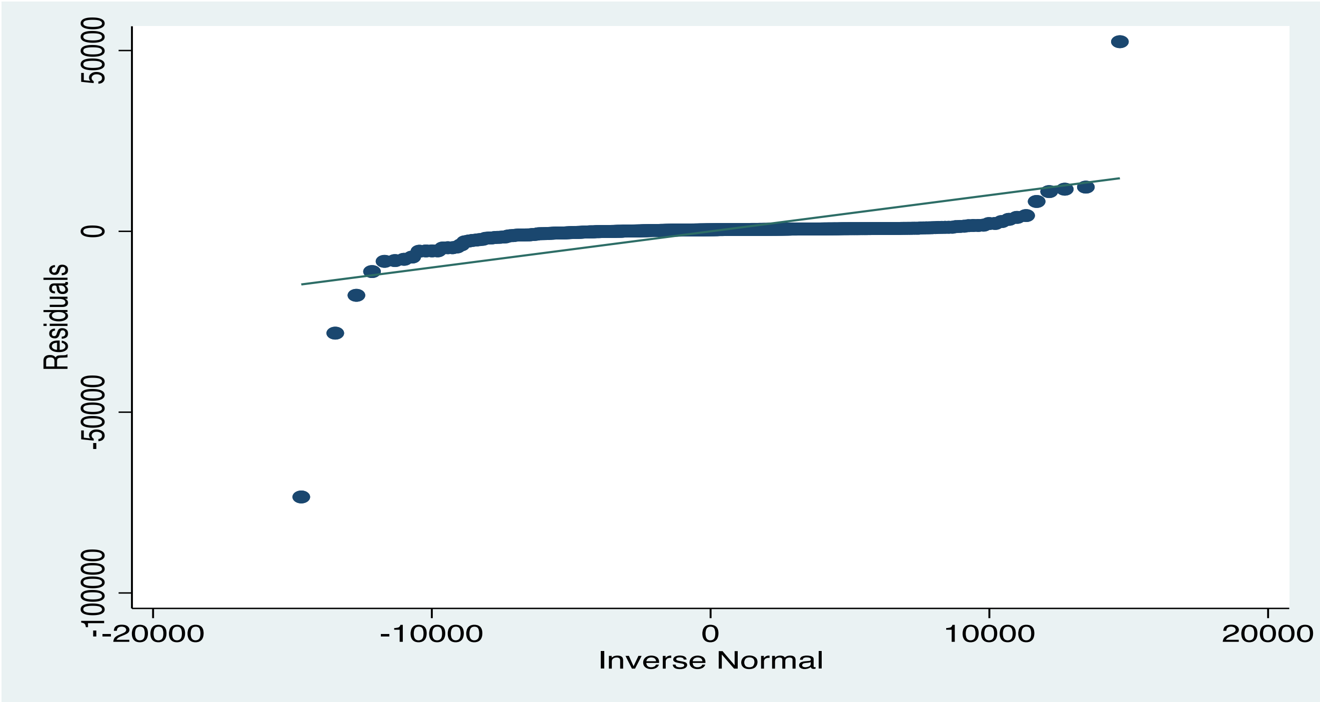

Table 13: residuals after log-transformation

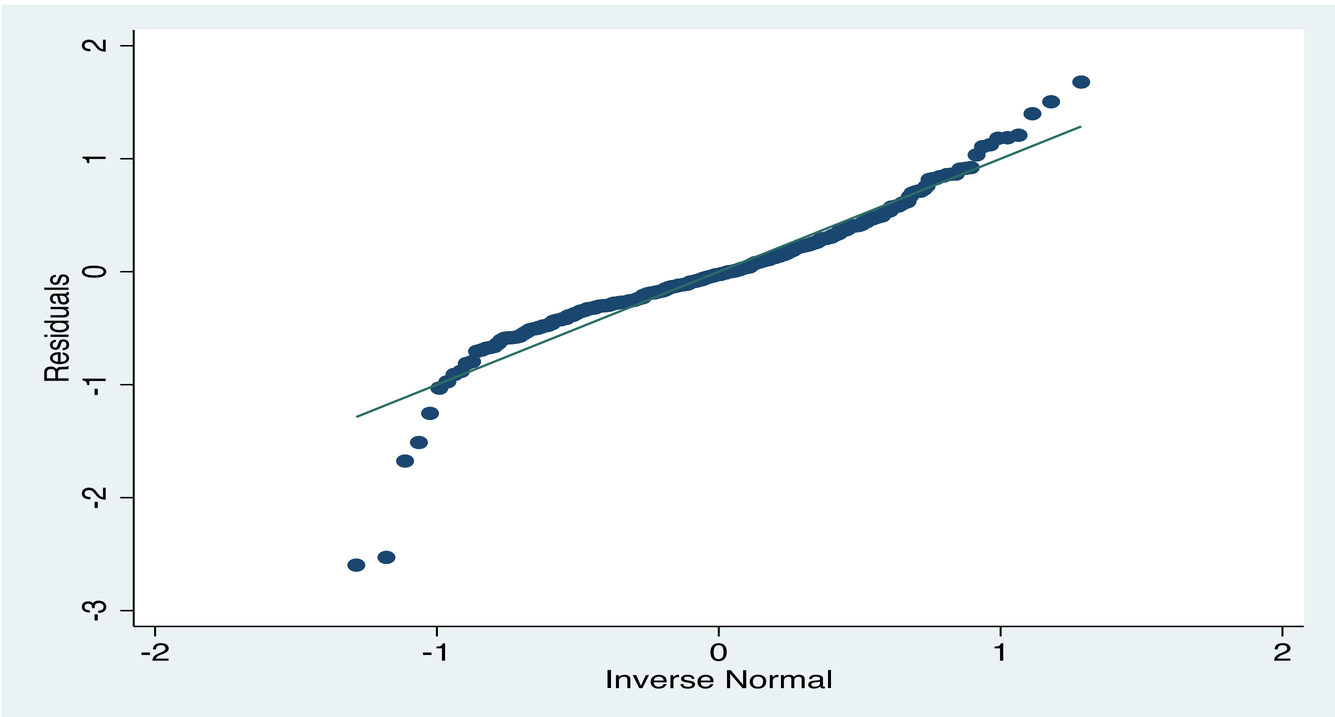

Table 14: OLS regression between BondPriceMoveDuring and MonthsIn

Linear regression

BondPriceMoveDuring	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MonthsIn	0.579	0.205	2.83	0.005	0.174	0.985	***
Constant	1.570	3.589	0.44	0.662	-5.521	8.662	

Mean dependent var	9.199	SD dependent var	29.705
R-squared	0.051	Number of obs	151.000
F-test	7.979	Prob > F	0.005
Akaike crit. (AIC)	1447.822	Bayesian crit. (BIC)	1453.856

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Table 15: Residual plot of the regression.

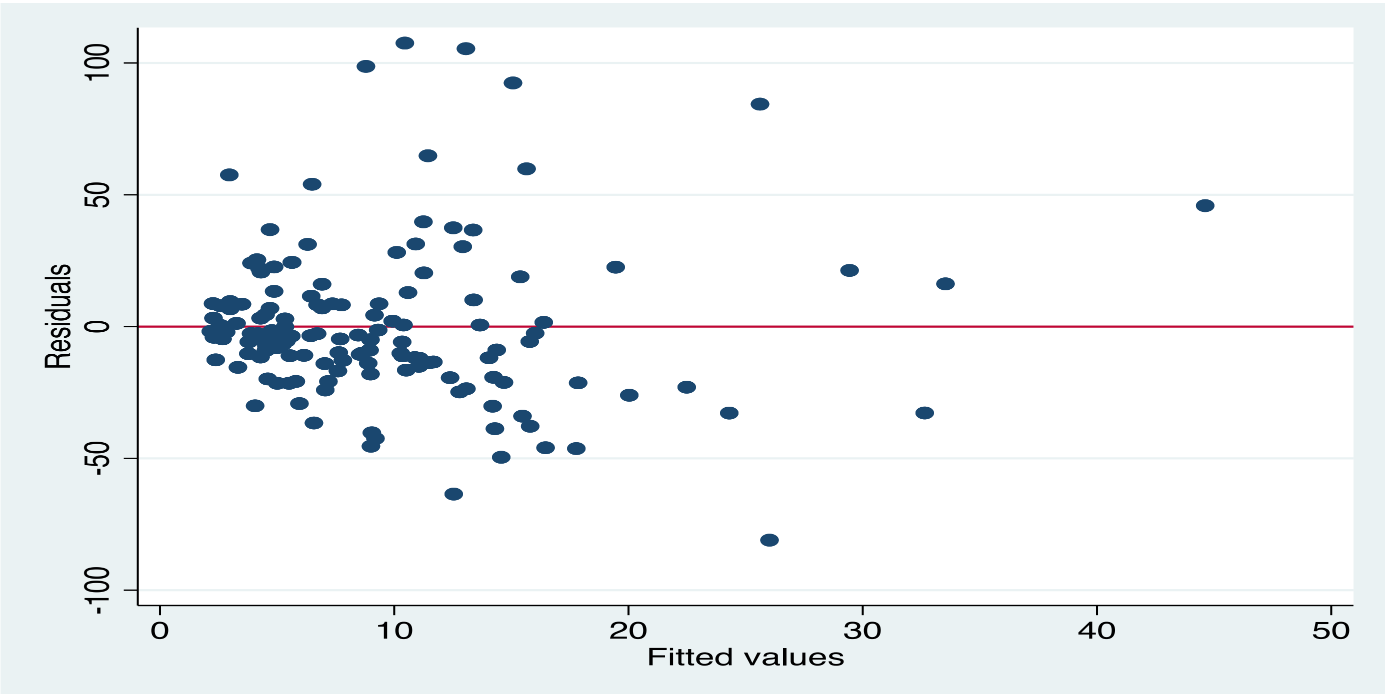

Table 16: OLS regression between ebitdaemerging and MonthsIn

Linear regression

ebitdaemerging	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MonthsIn	3.418	1.074	3.18	0.002	1.305	5.531	***
Constant	73.536	27.013	2.72	0.007	20.411	126.662	***

Mean dependent var	128.014	SD dependent var	518.900
R-squared	0.013	Number of obs	358.000
F-test	10.121	Prob > F	0.002
Akaike crit. (AIC)	5490.627	Bayesian crit. (BIC)	5498.388

*** *p<0.01, *** *p<0.05, * p<0.1*

Table 17: Financial outlook of companies we possess before and after bankruptcy filings.

Variable	N	Mean	Std Dev	Min	0.25	Median	0.75	Max
workingKbefore	304	-245.72	5170.8	-8.5e+04	-162.26	15.91	177.39	14217.00
workingKemerging	304	676.39	2238.9	-1184.15	47.42	135.30	442.57	28955.00
assetsbefore	304	3201.26	8902	155.05	410.95	954.80	2275.74	91047.00
assetsemerging	304	2801.14	9840	4.54	299.03	643.50	1630.57	1.4e+05
liabbefore	304	3446.98	12016	17.67	425.43	934.21	2307.77	1.8e+05
liabemerging	304	2124.76	7788.43	0.32	212.73	463.69	1069.48	1.1e+05
ebitbefore	304	-122.27	959.53	-1.2e+04	-61.10	1.36	49.15	2821.10
ebitemerging	304	20.62	779.09	-1.2e+04	-11.37	11.31	52.82	3068.00
salesbefore	304	2481.08	9596.25	1.24	352.21	647.57	2136.63	1.5e+05
salesemerging	304	2149.47	8843.73	0.00	235.01	582.52	1473.31	1.4e+05

Table 18: Financial outlook of companies we possess before and after bankruptcy filings for manufacturing firms.

Variable	N	Mean	Std Dev	Min	0.25	Median	0.75	Max
workingKbefore	105	-815.56	8510	-8.5e+04	-190.86	-20.60	106.72	14217.00
workingKemerging	105	862.65	3176.08	-530.18	50.63	133.79	483.71	28955.00
assetsbefore	105	3089.10	9826.27	155.05	413.70	820.90	2280.55	91047.00
assetsemerging	105	3181.19	13689.49	4.54	306.84	613.18	1798.71	1.4e+05
liabbefore	105	3904.66	17444.4	164.04	410.00	906.00	2453.59	1.8e+05
liabemerging	105	2318.54	10640.5	0.32	223.84	479.90	1160.38	1.1e+05
ebitbefore	105	-41.55	1205.26	-1.2e+04	-20.42	15.80	67.21	1882.00
ebitemerging	105	-17.59	1256.44	-1.2e+04	2.70	17.91	61.26	3068.00
salesbefore	105	3856.46	15525.1	102.30	416.80	15.57	82248.30	1.5e+05
salesemerging	105	3448.39	14403.59	1.50	354.14	710.00	1500.98	1.4e+05

Table 19: Financial outlook of companies we possess before and after bankruptcy filings for non-manufacturing firms.

Variable	N	Mean	Std Dev	Min	0.25	Median	0.75	Max
workingKbefore	199	54.95	1616.6	-1.0e+04	141.80	-29.60	204.50	8169.10
workingKemerging	199	578.10	1531.2	-1184.15	41.81	140.10	439.68	10181.75
assetsbefore	199	3260.43	8399.0	159.50	408.20	979.40	2270.94	80448.90
assetsemerging	199	2600.62	7044.4	18.11	296.34	650.22	1512.98	60029.10
liabbefore	199	3205.48	7806.73	17.67	444.31	951.00	2270.55	72279.80
liabemerging	199	2022.51	5773.07	3.14	209.72	447.93	999.72	51627.70
ebitbefore	199	-164.86	800.42	-5119.26	-101.38	-10.23	43.58	2821.10
ebitemerging	199	40.77	313.84	-1236.33	-16.40	7.83	47.17	2250.00
salesbefore	199	1755.37	3576.30	1.24	291.63	565.00	2021.60	37028.00
salesemerging	199	1464.11	3057.77	0.00	175.66	469.75	1466.00	22697.00

Table 20: Altman's Z-score comparison before and after bankruptcy filing

Variable	N	Mean	Std Dev	Min	0.25	Median	0.75	Max
ZscoreA All firms	304	3.51	1.52	-9.17	2.61	3.82	4.47	7.12
ZscoreA manufacturing	105	2.71	0.75	1.35	2.27	2.53	2.96	5.08
ZscoreA non manufacturing	199	3.93	1.64	-9.17	3.69	4.19	4.72	7.12
ZscoreB all firms	304	2.48	3.02	-27.24	2.22	2.82	3.71	6.14
ZscoreB manufacturing	105	2.63	0.67	1.30	2.23	2.57	2.88	6.14
ZscoreB non manufacturing	199	2.40	3.70	-27.24	2.15	3.20	3.86	6.11

Table 21: Descriptive statistics for MonthsIn across all firms

Variable	N	Mean	Std Dev	Min	0.25	Median	0.75	Max
MonthsIn all firms	304	15.36	16.87	0.60	3.85	9.77	20.43	131.83
MonthsIn manufacturing	105	20.29	22.92	1.03	4.53	13.30	24.53	131.83
MonthsIn non-manufacturing	199	12.76	11.83	0.60	3.20	8.87	18.60	71.57

Table 22: Correlation between MonthsIn and profitability ratio post-bankruptcy

Pairwise correlations

Variables	(1)	(2)
(1) X33	1.000	
(2) MonthsIn	0.212*	1.000

* shows significance at the 0.05 level

Table 23: Regression between X33 and MonthsIn

Linear regression

X33	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MonthsIn	0.002	0.001	4.48	0.000	0.001	0.003	***
Constant	-0.047	0.018	-2.66	0.008	-0.082	-0.012	***

Mean dependent var	-0.010	SD dependent var	0.193
R-squared	0.045	Number of obs	304.000
F-test	20.082	Prob > F	0.000
Akaike crit. (AIC)	-146.940	Bayesian crit. (BIC)	-139.506

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Table 24: Regression between X33 and MonthsIn for manufacturing firms

Linear regression

X33	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MonthsIn	0.001	0.000	3.66	0.000	0.000	0.002	***
Constant	0.005	0.010	0.48	0.635	-0.016	0.025	

Mean dependent var	0.025	SD dependent var	0.082
R-squared	0.077	Number of obs	105.000
F-test	13.415	Prob > F	0.000
Akaike crit. (AIC)	-231.583	Bayesian crit. (BIC)	-226.275

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Table 25: Regression between X33 and MonthsIn for non-manufacturing firms

Linear regression

X33	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
MonthsIn	0.005	0.001	4.14	0.000	0.002	0.007	***
Constant	-0.087	0.029	-3.00	0.003	-0.144	-0.030	***

Mean dependent var	-0.028	SD dependent var	0.230
R-squared	0.056	Number of obs	199.000
F-test	17.175	Prob > F	0.000
Akaike crit. (AIC)	-29.325	Bayesian crit. (BIC)	-22.738

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

Table 26: Distribution of cases to judges by Year

Judge is coded as follows: 0 for all judge with less than 10 cases during our period, 1 for Peter Walsh, 2 for Mary Walrath, 3 for Burton Lifland, , 4 for Kevin Carey, 5 for Allan Groper, 6 for Kevin Gross, 7 for Christopher Sontchi, 8 for Robert Drain, 9 for Brendan Shannon, 10 for David Jones, 11 for Marvin Isgur and 12 for Stuart Bernstein.

Tabulation of YearFiled judge

	judge													
YearFiled	0	1	2	3	5	6	8	9	10	11	12	14	15	Total
2003	38	5	6	2	0	1	0	0	3	0	0	0	1	56
2004	22	1	1	1	0	0	0	0	3	0	0	0	1	29
2005	13	4	1	1	0	3	0	0	3	0	0	0	0	25
2006	6	0	1	1	3	2	0	0	0	1	0	0	0	14
2007	4	1	0	1	2	0	1	2	0	2	0	0	0	13
2008	13	3	2	2	5	1	3	2	1	2	0	0	1	35
2009	40	3	6	2	8	4	8	6	1	4	0	1	1	84
2010	14	2	1	1	3	1	2	1	1	1	0	0	1	28
2011	9	2	1	0	2	1	3	2	0	1	0	0	1	22
2012	13	1	1	0	1	1	1	1	1	1	0	1	2	24
2013	6	3	5	0	3	0	3	3	1	1	0	0	0	25
2014	9	1	0	0	1	0	1	2	1	2	0	0	0	17
2015	10	0	2	0	4	0	3	4	0	1	1	0	0	25
2016	12	0	5	0	4	0	4	2	0	2	6	3	3	41
2017	12	0	0	0	4	0	2	3	1	2	2	4	0	30
2018	3	0	2	0	0	0	3	2	3	0	0	5	0	18
2019	7	0	2	0	0	0	2	0	1	1	6	5	0	24
2020	22	0	2	0	0	0	0	2	3	0	14	14	0	57
2021	0	0	1	0	0	0	0	0	0	0	0	0	0	1
Total	253	26	39	11	40	14	36	32	23	21	29	33	11	568

Table 27: descriptive statistics of duration for each judge

Variable	N	Mean	Std Dev	Min	0.25	Median	0.75	Max
MonthsIn	555	11.78	13.31	0.60	3.87	8.33	15.33	116.53
All Other Judges	247	13.37	13.07	0.60	5.37	10.20	17.27	97.53
Walsh	26	16.38	19.57	1.20	4.77	9.47	16.87	89.70
Walrath	37	11.38	14.35	1.20	3.10	7.07	13.93	67.33
Lifland	11	10.27	10.23	1.60	4.47	5.13	14.80	34.23
Carey	40	11.13	10.00	1.37	3.48	9.12	14.72	44.10
Gropper	14	10.42	8.70	0.97	4.53	5.60	18.43	29.67
Gross	36	11.44	18.15	1.03	2.88	5.55	12.93	97.73
Sontchi	32	10.74	9.39	1.37	3.67	9.37	14.43	46.67
Drain	23	14.71	23.44	1.17	4.50	7.70	16.23	116.53
Shannon	21	9.30	6.83	1.20	4.43	8.40	14.97	24.80
Jones	26	4.22	3.31	1.03	1.57	2.87	5.80	13.13
Isgur	31	5.31	4.75	0.73	2.07	3.73	6.03	22.60
Bernstein	11	11.08	7.58	1.03	3.63	9.13	17.40	22.90

Table 28: Descriptive statistics of firm characteristics

Variable	N	Mean	Std Dev	Min	0.25	Median	0.75	Max
assetsbefore	593	4950.9	32190.79	212.22	452.14	934.25	2526.17	6.9e+05
ROAfiling	558	-0.21	0.37	-3.30	-0.25	-0.11	-0.02	0.53
Emplbefore	592	6704.5	17149.05	1.00	614.00	2100.00	5545.50	2.4e+05
Leverage at filing	593	1.07	0.59	0.25	0.81	0.96	1.17	6.15

Table 29: Correlation between the instrument and MonthsIn

Pairwise correlations

Variables	(1)	(2)
(1) MonthsIn	1.000	
(2) instrument1	0.108*	1.000

* shows significance at the 0.05 level

Table 30: Descriptive statistics for first instrument and MonthsIn

Variable	N	Mean	Std Dev	Min	0.25	Median	0.75	Max
MonthsIn	555	11.78	13.31	0.60	3.87	8.33	15.33	116.53
Instrument 1	555	11.78	2.85	3.86	10.94	13.31	13.40	16.99

Table 31: estimates of IV regression of lnassetsbefore

Instrumental variables (2SLS) regression

lnassetsbefore	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lnmonthsin	-0.190	0.091	-2.10	0.036	-0.368	-0.012	**
lnliabbefore	0.934	0.019	49.42	0.000	0.897	0.971	***
emerge	-0.267	0.074	-3.63	0.000	-0.412	-0.123	***
Constant	1.055	0.176	6.00	0.000	0.709	1.400	***

Mean dependent var	7.076	SD dependent var	1.241
R-squared	0.876	Number of obs	544.000
F-test	1306.575	Prob > F	0.000

**** p<0.01, ** p<0.05, * p<0.1*
Underidentification test (Anderson canon. corr. LM statistic): 27.465
Chi-sq(1) P-val = 0.0000

Weak identification test (Cragg-Donald Wald F statistic): 28.713
Stock-Yogo weak ID test critical values: 10% maximal IV size 16.38
15% maximal IV size 8.96
20% maximal IV size 6.66
25% maximal IV size 5.53
Source: Stock-Yogo (2005). Reproduced by permission.

Table 32: Regression of emerge

Logistic regression

emerge	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
instrument1	-0.059	0.036	-1.67	0.095	-0.129	0.010	*
assetsbefore	0.000	0.000	-1.54	0.122	0.000	0.000	
liabbefore	0.000	0.000	1.44	0.151	0.000	0.000	
Constant	1.652	0.438	3.77	0.000	0.794	2.510	***

Mean dependent var	0.717	SD dependent var	0.451
Pseudo r-squared	0.016	Number of obs	544.000
Chi-square	10.540	Prob > chi2	0.014
Akaike crit. (AIC)	645.741	Bayesian crit. (BIC)	662.937

*** *p<0.01,* ** *p<0.05,* * *p<0.1*

NB: We use do not use the log version of the instrument here to replicate the prior regression made.

Table 33: Regression of change of ebit

Linear regression

lnchangeebit	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
lninstrument1	-2.204	0.557	-3.96	0.000	-3.316	-1.092	***
Constant	2.558	1.385	1.85	0.069	-0.207	5.323	*

Mean dependent var	-2.881	SD dependent var	1.559
R-squared	0.192	Number of obs	68.000
F-test	15.669	Prob > F	0.000
Akaike crit. (AIC)	241.870	Bayesian crit. (BIC)	246.309

*** *p<0.01,* ** *p<0.05,* * *p<0.1*