

Distribution Agreement

In presenting this thesis as a partial fulfillment of the requirements for a degree from Emory University, I hereby grant to Emory University and its agents the non-exclusive license to archive, make accessible, and display my thesis in whole or in part in all forms of media, now or hereafter now, including display on the World Wide Web. I understand that I may select some access restrictions as part of the online submission of this thesis. I retain all ownership rights to the copyright of the thesis. I also retain the right to use in future works (such as articles or books) all or part of this thesis.

Tejas Kashyap

April 9, 2019

The Impact of Investment Banking Advisory in Chapter 11 Bankruptcy

by

Tejas Kashyap

Zhongjian Lin
Adviser

Department of Economics

Zhongjian Lin
Adviser

Samiran Banerjee
Committee Member

Frederic Bien
Committee Member

2019

The Impact of Investment Banking Advisory in Chapter 11 Bankruptcy

By

Tejas Kashyap

Zhongjian Lin

Adviser

An abstract of
a thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
of the requirements of the degree of
Bachelor of Arts with Honors

Department of Economics

2019

Abstract

The Impact of Investment Banking Advisory in Chapter 11 Bankruptcy

By Tejas Kashyap

After the dotcom bubble implosion from 2000 to 2002, the restructuring and workout business was not very active leading up to the mid-2000's. However, the Great Recession of 2007 tightened credit and consumer spending, and led to a wave of corporate defaults which were resolved in the courts under primarily Chapter 7 and Chapter 11 bankruptcy proceedings. Investment banking firms are often hired by corporations in Chapter 11 proceedings to assist in procuring financing so that the company may continue to operate while their business is restructured in the courts. A typical form of super-senior loan with special rights for creditors during the Chapter 11 process is a Debtor-in-Possession (DIP) loan. This study seeks to determine the relationship between macroeconomic factors, bankrupt company financial conditions, and financials of the investment banking advisor in several multi-factor models with 0-2 years of lag, to the size, LTV, and time to receive a DIP. The findings of this study show that while increasing and decreasing financial leverage of the institutional investment bank is linked to longer time for a company in Chapter 11, the size and LTV of DIP financing is more significantly affected by global macroeconomic conditions and corporate financial data, primarily net balance sheet liabilities and sales, upon entering bankruptcy.

The Impact of Investment Banking Advisory in Chapter 11 Bankruptcy

By

Tejas Kashyap

Zhongjian Lin

Adviser

A thesis submitted to the Faculty of Emory College of Arts and Sciences
of Emory University in partial fulfillment
of the requirements of the degree of
Bachelor of Arts with Honors

Department of Economics

2019

Acknowledgements

I would sincerely like to thank my advisor, Zhongjian Lin, and my committee members, Shomu Banerjee and Frederic Bien, for advising me patiently throughout the process of writing this thesis. I also give tremendous thanks to Dr. Robert O'Reilly, who assisted greatly with my data preparation. His help was instrumental and invaluable. Finally, I thank my friends and family.

TABLE OF CONTENTS

I.	BANKRUPTCY BACKGROUND	1
II.	INTRODUCTION	5
III.	RELATED LITERATURE	9
IV.	DATA	14
	A. Dataset Construction	14
	B. Variable Selection.....	17
V.	RESULTS	20
	A. Multicollinearities	20
	B. Overarching Model	21
	C. Macroeconomic Condition Model	22
	D. Distressed Corporation Conditions Model.....	23
	E. Investment Banking Advisory Model.....	25
	Total DIP Financing	27
	DIP LTV	27
	Time to Resolve Chapter 11.....	28
VI.	CONCLUSION	30
VII.	CITATIONS	31
VIII.	APPENDIX	34
	Table 1: Effect of Macroeconomic Conditions on DIP LTV and Total Days to Resolution.....	34
	Table 2: Effect of Company Conditions on DIP Sizing.....	35
	Table 3: Effect of Company Conditions on Bankruptcy Timing.....	36
	Table 4: Total Model vs. All Dependent Variables [Lag 0]	37
	Table 5: Total Model vs. All Dependent Variables [Lag 1]	39
	Table 6: Total Model vs. All Dependent Variables [Lag 2]	41
	Figure 1: Summary Statistics of Key Independent Variables of Interest.....	43
	Figure 2: Correlation of Macroeconomic Variables	44
	Figure 3: Correlation of Company Financial Characteristics	45
	Figure 4: Correlation of Investment Banking Characteristics.....	46
	Graph 1: Scatter Plot of DIP LTV vs. Debt-to-Asset Ratio.....	47
	Graph 2: Scatter Plot of Bankrupt Companies in Dataset, 2000-2018 (by Sector).....	48

I. BANKRUPTCY BACKGROUND

In the study of economics, the concept of a free market can be assumed in many models centered on the ways that United States corporations compete with each other. Free markets give the incentive for entrepreneurs to create businesses with capital, which can be provided by loans from institutions or people known as “creditors”. Without a flow of capital to start up a business, many businesses would not be able to produce a prototype or find employees from the onset (Jackson et al. 98). Mature corporations also find the need to take on loans to finance projects that they cannot pay for with their current cash flows. Thus, these corporations, or “debtors”, owe the amount of the loan, plus some interest, to their creditors whenever they are lent money.

Fundamental to the free market is the belief, by the creditor, that he/she will be paid back, or “made whole”. These creditors lend money with the belief that on the date the debt is due, the debtor corporation will have sufficient cash from stockpiled operating income or other assets to pay back the creditor. One could say that the creditor expects the asset value of the debtor corporation to exceed the notional amount of the loan given, on the day it is due, if the creditor is to be made whole.

Because we have assumed mostly unrestricted competition in the free market, potential creditors have many avenues to invest their funds, and it is the job of the entrepreneur, CEO, or executive to convince potential creditors that their product or corporation has high growth prospects, high gross margins, high barriers to entry, demonstrates economies of scale, as well as other factors that will be accretive to the value of the company on the day its debts are due, so that the creditor can be made whole. Additionally, the potential investment must be enticing enough to creditors so that they pull their attention away from other investments, like government bonds, ETFs, mutual funds, *et cetera*. Thus, the interest rate that the debtor owes the

creditor, on top of the value of the loan, must reflect a fair rate to the creditor so that they lend money to the debtor rather than their next best investment.

Due to the competitive nature of firms in the U.S. economy, however, not all companies fulfill the promises they make to investors, and not all company valuations become realized on the day that the debt is due (Jackson et al. 98). Because not all companies succeed, and many have taken on debt they can no longer pay, there is a need for an effective process by which creditors are dealt with in an ordered manner, and the company is able to continue operating while the assets and liabilities of the company in distress are sorted through so they can be divvied up to those that are owed. Normally, the executives of the company owe a fiduciary duty to the shareholders, the entities that own the company equity. However, in times of distress, the fiduciary duties of executives expand to include the creditors, those that own the company debt (Jackson et al. 102).

Within the scope of basic definitions outlined by Nigam and Boughanmi in their 2015 paper, bankruptcy is described as a two-way street. “Bankruptcy arises when a firm cannot meet its obligations and the creditors cannot resolve their competing claims without a collective proceeding” (1862). All creditors rely on the U.S. legal system to provide an ordered system by which each can maximize the return of money they are owed from a distressed company that can no longer pay. Globally, corporate bankruptcy can have many possible resolutions, but there exist two primary resolutions of financial distress.

The first is a liquidation, governed by Chapter 7 of the US Bankruptcy Code in the United States, where the creditors believe that the fair value of the assets of the company are worth more presently than any new debt or bankruptcy proceedings could net, and opt for a collection of the value of the credit they are owed from the sale of the debtor company.

Typically, the company is sold by assets to numerous buyers for a fraction of what the accounting documentation says they are worth, and the proceeds are used to pay the creditors, from most senior to least senior, on the capital structure. The second is a formal process to restructure the core business of the debtor company so that it becomes more efficient. Ideally, this process will create cash flows that will be sufficient to pay back existing debt obligations on a different timeline or with a different rate of interest than what was initially decided between debtor and creditor. This path can be undertaken when an asset liquidation will not result in the highest and best possible value to creditors. This second process is broadly defined in Chapter 11 of Title 11 of the US Bankruptcy Code.

In a review published by Patrick Bolton for the 2003 IMF Annual Research Conference, bankruptcy proceedings contain three key principles, agnostic of country where the proceedings are occurring (Bolton 56). The first is that the bankruptcy proceedings will address the “run for the assets” and “race to the courthouse” problem that would occur if no organized process and no stay on assets existed (Bolton 56). If bankruptcy proceedings did not exist, there would be multiple claims on the same assets from secured credit-holders and the act of liquidating assets with multiple parties competing to sell as quick as possible is not economically maximizing for all parties. Because there is a stay on the assets and creditors are dealt with sequentially, the “going-concern” value of the firm, i.e. the company value based on the present value of projected cash flows rather than the company value based on liquidation, can be maintained, and if a breakup occurs, it will be done in an economically-maximizing format. Second, there exists a waterfall of payment priority when a company structures its financial obligations. In a practical example, local property taxes have a priority lien over a mortgage. A property owner must pay his/her local property taxes before paying the mortgage, and in general, one cannot pay the

mortgage first. This is similar to the waterfall of credit claims. In a proceeding, creditors must be paid according to “absolute priority”, where lower-priority claimants only receive the residual value of whatever is left after the higher-priority claimants are made whole. Lower-priority claimants are compensated with higher interest rates when they purchase debt securities but take the risk of not receiving their principal back if a company ever becomes distressed or liquidates. Finally, Bolton writes that the bankruptcy proceedings “mandate the cancellation” of unpaid debts following liquidation to allow owners and managers to start afresh after any failed endeavor, once all creditor claims have been resolved (56).

These three general economic features of bankruptcy proceedings are manifested in three elements present in US Bankruptcy proceedings, according to Bolton (45). The first is a suspension of cash outflows by the company for debt repayments or individual debt-collection efforts while the proceeding is taking place, as a bandage to stem any hemorrhaging of cash that can be used to sustain operations. The second is an allowance for new financing to preserve the value of the firm and allow operations to continue. Finally, so that there is not a line of creditors around the block clamoring for compensation, there is a delegation by the court of negotiations to creditor committees to represent all of the individual creditors in each class of debt during the proceedings. The leader of each creditor committee can put forth their own plan of reorganization if the company’s plan for reorganization fails to be accepted by a majority of each tranche of debt-holders, from high priority to low.

II. INTRODUCTION

The main purpose of this study is to study Bolton's second element of US corporate bankruptcy: additional financing procured during bankruptcy. I will be examining debtor-in-possession loans (DIP loans), a type of financing given to distressed firms which has built-in properties and special creditor rights that make it less risky for potential lenders than otherwise normal (Dahiya et al. 260). DIP financings are governed by Section 364 of the Bankruptcy Reform Act of 1978 as a post-bankruptcy petition financing and may take on a litany of forms, including "unsecured revolving credit lines or unsecured loans" (Elayan et al. 907). The debtor-in-possession loan gives the creditor super-seniority in the waterfall of claims on debtor assets; effectively, when the proceedings are concluded, the DIP provider will be one of the first institutions paid back by the restructured company.

The DIP financing is a positive for the distressed company, as it provides an injection of capital to the company to fund business operations while the business is restructured at the courts. Additionally, according to Paul Zumbro, partner at Cravath, Swaine & Moore LLP, the DIP financing signals to both vendors and customers that the debtor will continue to remain in business while the Chapter 11 process continues (4). Sophisticated lenders of the DIP have examined the debtor's finances and have projected that the debtor is able to repay the loan, so the market typically reacts favorably to the announcement of a DIP (4). This sentiment is echoed by the findings of both Sandeep Dahiya (Dahiya et al. 266) and Maria Carapeto (Carapeto 23) in their respective papers.

The institutions that provide the DIP loan can be any investor with access to the bankruptcy proceedings, like large investment banks, and the company is advised on this financing by investment banks, who usually take some percentage of the total DIP size as

compensation. Notably, the investment banking advisor and DIP provider are not the same investment bank due to grey area in regulations on conflict of interest, according to Jeff Werbalowsky, chief executive of boutique investment bank Houlihan Lokey in 2008 (Rozens 5). There are nine public investment banks in my sample, and the majority are considered “boutique” banks, as opposed to the larger “bulge-bracket” banks like Wells Fargo and J.P. Morgan, which are usually DIP loan providers.

My thesis revolves around the question of the impact of the investment banking advisor on the size and loan-to-value of the DIP loan, as well as the timeline of the overall Chapter 11 proceeding. I assume that the investment banks differentiate each other by two factors: (1) financial status, including the value of assets, liabilities, revenues, and other metrics on the investment bank’s accounting documentation, and (2) management expertise, which is unobservable and a proxy for management alpha. Because it may take time for the characteristics of the investment bank to influence the type of deals that it does, I have applied lags of zero, one, and two years to the investment banking variables for simplicity.

However, the characteristics of the DIP are not only determined by the investment bank. Company conditions at the time of bankruptcy, including number of employees, revenues, balance sheet size, and other metrics, are important in determining the characteristics of the DIP. Additionally, Chapter 11 proceeding are influenced by the general state of the economy, where the court may be more debtor-friendly at different stages of the economic cycle. Thus, I attempt to fit an OLS model to estimate the size, loan-to-value, and timeline of the DIP loan on variables within the three following categories: (A) macroeconomic conditions, (B) corporate financial health, and (C) investment banking factors, which can be decomposed into (1) financial status, and (2) management alpha.

In this study, I utilize the UCLA LoPucki Bankruptcy Research Database (BRD), which consists of over 200 fields of data on each of the over 1,100 large, public company bankruptcies filed in the United States Bankruptcy Courts since October 1, 1979. I restrict my data to bankruptcies between 2008 and 2018 to encompass the full range of the credit and economic cycle for both distressed companies and investment banking advisors, while avoiding the market fluctuations of 2007. I utilize Dow Jones Factiva and Nexis Uni to manually locate the news articles for each bankruptcy that list the investment banking advisors and turnaround advisors contracted on the deal, not dissimilar to the methodology established by Dahiya et al. (2003). To gather information on the investment banks, I use Bloomberg BDH functions to compile historical information on different company composite metrics, as well as Factiva and 10K filings with the SEC to pull historical balance sheet and income state financials. Notably, the dataset was restricted to public investment banking advisors in the US and UK, as private investment banking advisors did not disclose financial information with the SEC.

The major findings and contributions of this paper are four-fold:

1. The prime rate of interest has a positive impact on the loan-to-value of DIP loans, as lenders must seek increasing yield as the prime rate and risk-free rate increase.
2. Company balance sheet size and top-line income have a positive impact on the size of DIP loan procured.
3. The leverage (debt-to-asset ratio) of the investment bank has a quadratic relationship with the time to complete Chapter 11. Middle leverage banks are associated with the fastest times to complete Chapter 11.
4. There is a demonstrated lag effect between variables related to the size of the investment bank and the LTV of DIP deals pursued.

I will likely observe collinearities between regressors within the company and at investment banks, as assets, liabilities, and sales theoretically should scale at a similar level as the overall balance sheet expands to generate more top-line revenue. I will run collinearity analyses to observe significant sources of multicollinearity to best choose my regressor variables.

III. RELATED LITERATURE

Research on debtor-in-possession financing began receiving popularity in the mid-1990s, likely due to the emergence of the modern U.S. bankruptcy system in 1978 with the adoption of the Bankruptcy Reform Act. According to Bolton, the 1980s saw an explosion of activity in the junk bond markets, as well as the appearance of leveraged buyouts by then-niche private equity players like KKR and TPG (46). The U.S. as a whole was giving more freedom to the debtor in cases of distress, so corporations felt more comfortable issuing junk bonds to raise funds if they knew there was a strong market demand for high yield, and that in a distressed scenario, they did not have an obligation to pay down unsecured debt claims at-cost if the liquidation value of their firm would not cover the debt (Bolton 44). A short series of financial crises in the 1980s and 1990s, notably, Black Monday in 1989, the early 1990s recession in the US after the Iraqi invasion of Kuwait, and importantly, the dot-com bubble burst in 2000, may have prompted research into the implications of the new Bankruptcy Law (44). Initial financial economic research related to the effect of financial distress, and subsequent DIP financings, on equity-market reactions with time-series analysis.

Elayan and Meyer (2001), published in the *Journal of Business Finance & Accounting*, was one of the first papers to examine the effect of DIP financing on the outcomes of financial distress. This paper sought to investigate the recent explosion in financial distress and tested the interaction between the reception of the DIP and a host of dependent variables, including market reaction and emergence from Chapter 11. The paper found that equity returns in the two days after the announcement of the DIP were positive and statistically significant, following a worsening market reaction 4 and 5 days before the announcement of the DIP. Additionally, this paper found that the success rate for firms that receive DIP financing is 87.50%, compared to a

71.25% rate for firms that do not. With regards to bankruptcy duration, a variable I intend to regress, Elayan and Meyer found that the reception of the DIP reduced the length of time in bankruptcy by 98 days, significant at the 10% level. These results were adjusted to incorporate the size of the DIP, but while the size of the DIP changes inter-group time in bankruptcy, controlling for size effect does not change the results between DIP and non-DIP financed firms. However, the authors caution that there may be an untestable “causal link” between a firm receiving DIP financing and recovery from bankruptcy (911). The authors acknowledge the possibility that Chapter 11 firms which receive such financing are considered more likely to recover in the first place, so it is their implied business qualities rather than the DIP that lead to successful emergence.

Following the work of Elayan and Meyer (2001), Dahiya, John, Puri and Ramirez (2003), published in the *Journal of Financial Economics*, confirmed much of the research of Elayan and Meyer, but used a significantly more expansive dataset and more robust analyses. The paper draws on Bankruptcy DataSource (BDS) and cross-lists SIC codes from firms identified in BDS with the Dealscan database from the Loan Pricing Corporation, as well as the Dow Jones News Retrieval system and the Lexis-Nexis business news section for key words. Through this exhaustive manual approach, Dahiya et al. identified 538 Chapter 11 filings, of which 165 received DIP financing, from 1988 to 1997.

Dahiya et. Al repeated Elayan and Meyer’s test for emergence, estimating a Probit model to variables related to the balance sheet characteristics of the bankrupt firm. Specifically, this paper identifies the natural log of total assets, the company’s leverage ratio, and the current asset ratio, as variables of interest, while also including dummy variables for retail firms, firms that declared bankruptcy after 1992, firms that received a DIP, and prepackaged bankruptcies. This paper finds

that larger firms with greater assets are more likely to emerge from bankruptcy, while a larger current asset (cash) balance is associated with lower probabilities of emergence at 1% significance. The paper speculates that a larger proportion of current total assets implies that “the liquidation value of such a firm is likely to be higher, as current assets have lower liquidity costs as compared with fixed assets (271).” This means that current assets, like cash and short-term investments, can easily be converted into funds to pay down investors in a Chapter 7 liquidation, while a company with a greater proportion of long-term assets (plants, property, equipment, land, etc.) will be more likely to be taken through the Chapter 11 process. As demonstrated by Elayan and Meyer (2001), the paper confirms at 5% significance that receiving a DIP is accretive to emergence. However, this paper is still presented with the conundrum of Elayan and Meyer (2001), where the “causal link” causes uncertainty on the true source of emergence. Using an advanced two-step selectivity method with an inverse mills ratio, this paper finds that DIP financing can be attributed as a positive relation to the probability of emergence.

Next, the paper attempts to fit a Probit model to the dependent dummy variable on the firm’s ability to procure a DIP. All independent variables used in the emergence Probit model remain, excluding whether or not the firm received the DIP. Findings significant at the 1% level indicate that companies with larger asset pools and a greater ratio of current assets are more likely to obtain DIP financing, but do not monitor how these variables interact with the size of the DIP financing itself. This paper also performs a novel inside versus outside creditor Probit analysis, by examining if the DIP creditor has previously lent money to the company (an “insider”). The paper finds that smaller firms are more likely to obtain DIP funding from preexisting lenders, likely due to informational advantage in smaller companies.

Additionally, this paper estimates an OLS model with the same independent variables on the time to emergence. The authors find that that the coefficient on reception of the DIP is negative and significant at 5% confidence. This is consistent with prior literature demonstrating that the reception of the DIP is related to a faster resolution.

A working paper published for Cass Business School by Maria Carapeto in 2003 followed-up upon the analysis of Elayan and Meyer but used a larger dataset of 326 publicly traded firms that filed for Chapter 11 between 1986 and 1997. Carapeto estimated a logistic model to establish that the reception of DIP financing, a dummy variable, was driven by a measure of liquidity or profitability, as confirmed by Dahiya et. Al (2003). She utilized financial metrics like income/assets, revenue/assets, and the current assets to total assets (CATA) ratio. As expected, more profitable firms are correlated with reception of DIP financing. However, she includes dummy variables to flesh out the influences of CEO turnover, prepackaged bankruptcy, and having the bankruptcy in Delaware, a “debtor-friendly” district.

Additionally, Carapeto examined the influence of company variables on emergence of the Chapter 11 company from bankruptcy, using a logistic model to estimate the impact of these variables on a dummy variable representing emergence. Once again, profitable firms with greater income/assets were more likely to emerge from bankruptcy, as they were more successful in the first place. Additionally, Carapeto found that greater company leverage and number of creditor classes is associated with successful reorganization, as the creditors are beholden to “push” the company through bankruptcy so that they may recover increased value for their investment. Additionally, as expected, a greater time spent in Chapter 11 is linked to a greater probability of emergence.

Moreover, Carapeto estimated eight OLS models assessing return rates for different classes of claimants – i.e. secured creditors, unsecured creditors, and equity holders. Larger and more profitable firms (greater asset balances) were found to distribute greater recoveries to all asset classes. Additionally, she finds that the presence of the DIP reduces recovery rates for all classes but increasing relative size (DIP loan-to-value of debt) was related to increased recovery for all classes. Finally, the presence of the DIP is greatly associated with a lower probability of liquidation, where debt claimants fare poorly.

Later papers continue to monitor the effect of DIP financing and market interactions at deeper levels. Chatterjee, Dhillon, and Ramirez (2004) analyze both stock and bond returns, using a similar methodology to Elayan and Meyer (2001), concluding that “positive stock price reactions to DIP loan announcements reflects the benefits of DIP financing. (3104)” Additionally, this paper examines the structure of the DIP facility and type of covenants, either affirmative or negative, and how these covenants affect the debtor. Ivashina, Iverson, and Smith (2015) also create a novel dataset of 136 bankrupt companies between 1988 and 2009 and found that distressed firms with concentrated creditor ownership are more likely to be successful in the bankruptcy process, with either a prearranged bankruptcy plan or a quick pass through Chapter 11. They also examine how ownership (“insiders”, according to Dahiya, et al.) on the company’s capital structure changes during bankruptcy, where higher ownership concentrations within a debt class is associated with higher recovery rates to that class.

My analysis will diverge from previous literature as I examine the impact of investment banking on the debtor-in-possession financing, rather than examining market effects due to the DIP. No literature before has examined precisely what my analysis encompasses, so some of my findings will not be confirmed in the literature.

IV. DATA

The following data was assembled from a variety of sources. First, I used the UCLA LoPucki Bankruptcy Research Database (BRD), under the UCLA School of Law, downloaded and last updated on February 3, 2019. This dataset contains approximately 200 columns of financial and case information on the bankruptcies of 1,129 US public corporations which report total assets of \$100MM or more in 1980s dollars. The database contains six major segments of data: (1) company identifiers, (2) case identifiers, (3) company characteristics, (4) case characteristics, (5) case outcomes, and (6) general economic conditions.

A. Dataset Construction

I was required to construct two additional datasets to supplement the BRD. The first was a dataset that associated the name of each bankruptcy with the investment banking advisor and turnaround advisor, if there was one, for each deal filed between the years 2008 and 2018, inclusive. My methodology was to first perform an advanced search for news articles in the database Nexis Uni, of the form: (“NameCo” AND “Advisor” AND “Bankruptcy”), where NameCo is the name of the distressed company in question. This strategy is validated in the literature by Dahiya et al. (2003). I would then manually scan all relevant articles for the name of the investment banking/financial advisor. If this search failed to reveal anything, I would repeat the search in the Dow Jones Factiva database. If the company had multiple bankruptcies listed in the BRD, indicated by the year in parenthesis in the NameCo variable column, I would ensure that the year of the bankruptcy matched to the year the article was published, or that

contents of the article pointed to the bankruptcy being either the first or second of the company in question.

In the case that this first search failed, I would repeat the advanced search for articles, first in Nexis Uni, then Dow Jones Factiva, of the form: (“NameCo” AND “DipAtty”), where DipAtty represented the first word of the name of the legal team contracted on the transaction. The legal team was almost always listed in the BRD for target companies. If a news article listed the name of the debtor attorney, I would search the article for the name of the debtor financial advisor, which was usually listed nearby within the article.

Next, I organized and merged this data to my original dataset with Stata, using NameCo as the merging variable. Because approximately half of the investment banking/financial advisors found through the above methodology resulted in non-public investment banks, I stripped out these results to select only distressed corporations that contracted public investment banking advisors that issued their initial public offering during or before the period 2008 to 2018. These investment banking advisors were (1) Blackstone Advisory Partners (ticker = BX), (2) Evercore (ticker = EVR), (3) Houlihan Lokey (ticker = HLI, IPO in 2014), (4) Jefferies (ticker = JEF, subsidiary of Leucadia), (5) Lazard (ticker = LAZ), (6) Moelis & Co. (ticker = MC, IPO in 2014), (7) PJT Partners (ticker = PJT, IPO in 2015), (8) Rothschild (ticker = ROTH, traded on Euronext), (9) Miller Buckfire & Co. (ticker = SF, subsidiary of Stifel Financial Corp.). Because three banks issued their IPO, and thus began submitting reports with the SEC, in a year between the dates of my study period, I stripped all companies that engaged the investment bank in a year that it was non-public.

With this manual analysis, I found 198 companies which filed for Chapter 11 bankruptcy between the years 2008 and 2018 that had listed public financial advisors. Next, I created a

database of financial information about the investment banks during the years that they were public. I designed functions in the Bloomberg Excel Plug-In of the form BDH(“ticker”, “financial”, “startdate”, “enddate”, “currency”, “period”). The “ticker” was the Bloomberg-specific company identifying ticker, the “financial” was the metric I was interested in, and the other metrics were added to ensure my dataset was consistent with yearly fiscal data in US dollars. To find specific balance-sheet metrics, I utilized FactSet to download financial information for every year within my date range that each bank was public. My variables of interest were total assets, total liabilities, cash and short-term investments, total debt, and the debt-to-asset ratio, which was calculated as total liabilities divided by total assets as a proxy for financial leverage of the investment bank.

I additionally manually constructed a dataset that contained the total revenue of the corporation or parent, and the percent of this revenue derived from advisory services. Because both Miller Buckfire and Jefferies were subsidiaries of much larger corporations, the breakdown of advisory versus other forms of revenue was not always clear or consistent. I cross-checked these metrics between FactSet and SEC filings to maintain accuracy in the dataset. Additionally, Moelis did not categorize revenue as advisory or otherwise, so I made the assumption that all of Moelis’ revenue comes from advisory services, given that their SEC filings does not indicate other significant sources of revenue.

Notably, Rothschild is the only corporation in my dataset that was not headquartered in the U.S., and thus did not always follow SEC financial reporting standards. However, the global variables I sought to find from both Bloomberg and FactSet were verified accurate by examining their financial statistics on the Rothschild investor relations portal.

The BRD provides information on GDP, CPI, and the prime interest rate on the date of the Chapter 11 filing for each company. To supplement this macroeconomic data, I downloaded daily West Texas Intermediate (WTI) crude oil prices (non-seasonally adjusted) from the Federal Reserve Bank of St. Louis (FRED) and calculated the mean, median, and end of year pricing for each year from 2008 to 2018.

I then utilized Stata to organize and merge the FactSet, Bloomberg, Percent Revenue from Advisory, and WTI oil datasets with each other, according to the bank ticker and fiscal year of the financial information, and then merged this final dataset with the BRD according to the name of the investment bank and the year of the Chapter 11 filing.

A summary of my independent variables is provided in Figure 1.

B. Variable Selection

My research will build upon previous research but will not examine the impact of the DIP on equity returns or differentiate firms based on whether they receive or do not receive a DIP.

Dependent variables for my OLS modelling consisted of four calculated financial metrics from the BRD. The first, DIP size, was calculated as the sum of all DIP values in the BRD to produce an overall amount of funding provided during the bankruptcy. The majority of companies in distress receive one DIP, but some companies can receive two or more from different lenders. Thus, to provide an accurate picture of the total amount of funding given to the distressed companies, these values were summed. This value will be log transformed in my OLS models.

The second metric, DIP risk, was estimated by dividing the total DIP size by the pool of assets the company reported on their last 10K report. This value can also be referred as a loan-to-value, or LTV, as the loan value is expressed as a fraction of the value of the underlying

company assets. According to the literature (Dahiya et. Al 2003), this is a standard and theoretically acceptable form of calculating the risk of a transaction.

The third and fourth metrics dealt with the time to completion for the DIP and bankruptcy, respectively. The first metric was the length of time from the filing date to the date the court entered its final order approving the DIP loan. The second metric was the length of time from the filing date to the case disposal date – the earlier of the date where the reorganization was confirmed, or the date where the case was converted to a Chapter 7 case or dismissed. I will log transform both of these variables in my OLS models.

I also conducted a Probit analysis on a fifth dependent variable, the emergence of the distressed company from Chapter 11. Because this type of analysis has been well documented in literature on the full dataset with regards to the influence of corporate and bankruptcy conditions on emergence, especially by Carapeto (2003), I restricted the Probit analysis to just the 198 companies in my dataset. A company is considered to have emerged by the BRD if at least one operating company emerged from the bankruptcy under either a confirmed plan or 363 sale. My analysis is novel because it estimates the impact of the investment banker on emergence of the company, a model which has not yet been examined in the literature.

The independent variable selection was formed based on the literature and the data available. Variables that related to the economy were provided by the BRD and encompassed GDP, CPI, and the WSJ prime rate of interest on the date of filing, as well as the WTI crude oil prices from the St. Louis Fed. Variables that related to the company in distress were provided by the BRD and encompassed basic balance sheet and income statement aggregate items, including total assets, total liabilities, and sales, and also included employee headcount on the date of filing. Variables that related to the financials of the investment bank pooled from SEC filings,

Bloomberg, and FactSet, included balance sheet and income statement line items, including total assets, total liabilities, cash and short-term investments, total debt, and revenues, as well as the number of employees, the market cap, the weighted average cost of capital, and the price-earnings ratio.

V. RESULTS

A. Multicollinearities

When performing multiple OLS regression, it is important to check collinearity between regressor variables. I examined collinearities for the three pools of regressor variables, shown in Figures 2, 3, and 4 in the Appendix at 5% significance.

Because CPI and GDP are significantly positively correlated, my macroeconomic models will be estimated using the Prime Filing Rate and GDP only.

Regarding the company specific characteristics, it is clear that EBIT, EBITDA, assets and liabilities are significantly positively correlated. Thus, I will only use one of these characteristics as an estimate for balance sheet size. Employee headcount generates sales, which means the two are significantly correlated, and net income has a negative correlation with assets, liabilities, and sales. Because sales are capital structure agnostic, I will use this metric and will not use net income or other income statement metrics. I will also only use either total liabilities or total assets as predictor variables. Because these variables are only needed for the purpose of demonstrating the company's financials, I will select one item from the income statement, one item from the balance sheet, and employee headcount in my regressions.

Regarding the investment banking variables, all balance sheet items (assets, liabilities, cash) are significantly correlated with each other as well as sales. Higher WACC companies are typically riskier, and typically smaller (smaller asset and liability pool), as seen in Figure 3. Because of this, I will only use one balance sheet metric in my regression, and will not use WACC, due to the strong correlation with my balance sheet data.

B. Overarching Model

I estimate the response of the four response variables through segments of the following overall OLS regression model:

$$y = \beta_0 + [\beta_1 \dots \beta_i] \cdot [econ_1 \dots econ_i] + [\theta_1 \dots \theta_j] \cdot [company_1 \dots company_j] \\ + [\omega_1 \dots \omega_k] \cdot [ib_1 \dots ib_k] + \varepsilon$$

Each of the vectors $[\beta_1 \dots \beta_i]$, $[\theta_1 \dots \theta_j]$, $[\omega_1 \dots \omega_k]$ represent a vector of coefficients from the OLS regression for each of the three categories of independent variables I will be examining. The dot product of these vectors and the variable vectors produces an overarching OLS model which I seek to determine in the final section of these results.

$[econ_1 \dots econ_i]$ represents a vector of i variables related to the state of the US economy at the time of bankruptcy filing, including the prime rate of interest, the price of oil, and the US gross domestic product. $[company_1 \dots company_j]$ represents a vector of j variables related to the financials of the distressed corporation at the time of bankruptcy filing, including sales, assets, and liabilities. $[ib_1 \dots ib_k]$ represents a vector of k variables related to the financial condition of the investment bank contracted by the company as financial advisor at the time of the bankruptcy filing. Notably, lags of zero, one, and two years will be applied to these investment banking variables to estimate any lag in the time for the characteristics of the bank to “trickle down” into the type of deals pursued. The error term, ε , contains the unobserved investment banking management ability, or alpha, as well as other unobserved variables. Investment banks differentiate themselves by their financial capabilities (assets, leverage, percent revenue from advisory, etc.), but also by their managing directors who bring in deals. Because no data exists on specific management alpha across investment banks, the error term will contain this unobserved management ability alongside other unobserved variables.

C. Macroeconomic Condition Model

I estimate the response of the four response variables, denoted by vector y , through a series of linear OLS regression models:

$$y = \beta_0 + \beta_1 * primeinterest + \beta_2 * GDP + \beta_3 * oilprice$$

primeinterest is the prime rate of interest on the bankruptcy filing date, drawn from the Wall Street Journal Prime Rate History

GDP is the Gross Domestic Product for the quarter in which the case was filed

oilprice is the West Texas Intermediate (WTI) crude oil prices (non-seasonally adjusted) from the Federal Reserve Bank of St. Louis (FRED), either end of year price or median yearly price

Table 1 holds the results from the regression of DIP LTV regressed on these economic factors. Results from Table 1 indicate significant values that align with current findings in the literature at 1% significance. A 1% increase in the prime rate of interest at filing is expected to increase the LTV of the DIP-to-asset by 7.1% in Model 1. As the prime rate of interest increases, buoyed by a rising risk-free rate during contractionary monetary policy, investment banks must complete more high-risk deals to increase returns for investors of the investment bank equity over that of the rising risk-free rate. Additionally, during a swell in the economy, creditors are more comfortable making larger loans to at-risk companies with the same asset pools as during the post-recessionary period. Finally, as the prime rate of interest increases, commensurately the rate of interest that the DIP pays must too increase, to compensate the DIP providers for the risky investment. However, this innately makes the value of the DIP “riskier” and should theoretically be marked by an increase in loan-to-value as credit rates rise.

Table 1 also holds the results from the regression of total days to complete bankruptcy, log transformed, regressed on the same economic factors. Results indicate significant values that have not yet been explored in the literature. There is a significant negative relationship between GDP and time to complete bankruptcy proceedings at 1% significance, where an increase of GDP by 1 (2012 = 100 on the index) decreases the time spent in bankruptcy by 5.7 days in Model 6. I conjecture that when economic conditions are poor in the US economy, GDP drops and bankruptcy proceedings take longer, as the various creditor parties will argue more extensively to extricate maximum value from the transaction if their other investments are performing poorly. This was likely the case in 2008-09, after the financial crisis.

D. Distressed Corporation Conditions Model

I estimate the response of the four response variables, denoted by vector y , through a series of linear OLS regression models. Note that the model was run twice, with Assets instead of Liabilities, to ensure the results are significant for both measures of a company balance sheet.

$$y = \theta_0 + \theta_1 * \ln(Liabilities) + \theta_2 * NumEmployees + \theta_3 * \ln(Sales)$$

Liabilities is the total liabilities from the last 10-K filed before bankruptcy, in millions of USD, log transformed

NumEmployees is the number of persons employed by the debtor as of the last 10-K before filing; includes both part time and full-time employees

Sales is the sales listed on the last 10-K filed before bankruptcy, in millions of USD, log transformed

Table 2 holds the results from the regression of DIP size, log transformed, over corporate conditions upon bankruptcy filing. Results from Table 2 indicate highly significant values for $\ln(\text{Liabilities})$, $\ln(\text{Assets})$, and $\ln(\text{Sales})$ coefficients at 1% significance, and for the number of employees at 5% significance. Model 6 (adjusted R-squared = 57.9%) points to positive coefficients on all variables, indicating that larger companies, in balance sheet and headcount, receive larger DIPs. This result is heavily supported by literature and contemporary corporate financial thought. Larger companies with greater balance sheets and sales are viewed as safer investments by potential DIP creditors. A large base of liabilities indicates a commensurately large asset base to cover the additional DIP liability, and high values for top-line sales are indicative of a company that is able to generate cash flow to pay down debt, but one that may need to trim margins by cleaning costing inefficiencies. If the company fails to emerge from Chapter 11, DIP providers will have a large asset base to be made whole from at a larger company than a smaller company.

Tables 3 holds the results from the regression of total length of time to complete Chapter 11 proceedings and total length of time to receive a DIP after filing (both log transformed) over the company characteristics. There was a statistically significant relationship between the size of balance sheet and the time to resolve Chapter 11. An 100% increase in either assets or liabilities would increase the number of days in bankruptcy by 15.3 and 13.2 days, respectively, according to Models 5 and 6. If a company has more liabilities or assets to review during a restructuring, the bankruptcy proceedings will take more time.

I hypothesized that the number of employees would be significant at a 1% level, but it appears that the balance sheet considerations and company financing are more significant to length of time spent in DIP than the company headcount. I found a significant quadratic

relationship between company balance sheet and the time to receive a DIP. Companies with smaller and larger balance sheets see their time to receive a DIP reduced, while those medium-size companies have longer waiting periods to receive a DIP. One possible explanation is that while larger companies are in greater need of DIP financing as soon as possible to continue operating, smaller companies are less complex to understand and therefore receive financing faster. Dahiya et al. (2003) has explored this result for insider versus outside creditors. That paper finds that smaller firms tend to obtain DIP financing from existing lenders, due to information asymmetries. In this case, smaller companies may receive a DIP faster due to their pre-existing inside creditors.

E. Investment Banking Advisory Model

I estimate the response of the four response variables, denoted by y , through a series of linear OLS regression models of the form:

$$y = \beta_0 + \beta_1 * primeinterest + \theta_1 * \ln(Liabilities) + \theta_2 * NumEmployees + \theta_3 * \ln(Sales) + \omega_1 * Leverage + \omega_2 * Leverage^2 + \omega_3 * Cash + \omega_4 * PercentAdvisory + \omega_5 * NumEmployees$$

primeinterest is the prime rate of interest on the bankruptcy filing date, drawn from the Wall Street Journal Prime Rate History

Liabilities is the total liabilities from the last 10-K filed before bankruptcy, in millions of USD, log transformed

NumEmployees is the number of persons employed by the debtor as of the last 10-K before filing; includes both part time and full-time employees

Sales is the sales listed on the last 10-K filed before bankruptcy, in millions of USD, log transformed

Leverage is the ratio of total debt to total assets, expressed as a percentage, listed on the bank's 10-K, obtained from FactSet

Cash is the total cash and short-term liquid investments listed on the bank's 10-K, obtained from FactSet

PercentAdvisory is the ratio of total revenue from investment banking advisory to the total revenue of the bank, expressed as a decimal, listed on the bank's 10-K in the supplemental notes

NumEmployees is the number of employees employed at the bank, obtained from Bloomberg

Under Graph 1, the justification for the squaring of the Debt-to-Asset, or Leverage, ratio is found. There appears to be a quadratic relationship between DIP Risk and Leverage Ratio; at both low and high leverages, investment banks pursue riskier transactions. Because there is no literature on the relationship of the investment banking financials to the risk of the deals they pursue, this result is novel. It is logical that as the investment banking leverage increases, they must pursue riskier deals to generate enough profit to pay off their own debt when it matures. By doing riskier deals, they are obtaining a larger portion of the advisory fee from a smaller body of assets, but there is a chance that the bank may develop a reputation for sandbagging a company with too much leverage and future companies will turn to their competitors. Middle-leverage banks may be at a transition period as they increase or decrease leverage, and because they are changing the extent to which they are levered, pursue lower LTV deals until they establish either lower or higher leverage.

Because it is possible that the characteristics of the investment bank take some time to trickle into shaping the risk of the deals the bank pursues, I examine these characteristics during the year of filing (no lag), the year before filing (lag 1 year), and 2 years before filing (lag 2 years).

Total DIP Financing

Generally, in the year of the bankruptcy, corporate features dominate in determining the size of the DIP procured. The coefficients on company liabilities, sales (both log transformed) and employees are positive and significant, indicating that larger companies with greater balance sheet, sales and employees are more likely to receive a larger DIP. This is backed by the literature; Carapeto (2003) indicates that a measure of liquidity or profitability is a significant positive determinant in whether a company receives DIP financing, but here I find that the size of DIP financing is also shaped by corporate conditions. I find that the investment bank does not have a significant influence on the size of the DIP procured at any lag value in the total model.

DIP LTV

The prime interest rate has a significant and positive coefficient on the DIP loan-to-value, which can be understood that as the Federal Reserve practices contractionary monetary policy and increases interest rates, the prime rate of interest also increases, and riskier DIP deals are given to companies to increase returns to DIP providers. Large investment banks that provide a DIP will not engage in the transaction if the returns are not sufficiently higher than the risk-free rate, the rate at which one can generate interest without risk by investing in US Treasury Bonds or Bills. Thus, to establish higher returns, the value of the DIP per the assets on the company

balance sheet must be increased to generate higher-valued interest payments from the company on the debt.

I also find that the coefficient on log Company Liabilities is negative and significant, indicating that larger companies receive smaller proportional DIPs compared to smaller companies. Once again, there may be some demonstrated insider versus outsider effects at smaller companies, where inside lenders have an information asymmetry and feel comfortable lending larger sums to increase the probability of emergence.

Notably, at two years of lag, the coefficients on investment banking headcount and percent revenue derived from advisory are positive and significant at the 10% level. This indicates that as banks scale up their overall size and investment banking arm, they have the capability to perform riskier deals some time later after these changes begin to take effect. It is unknown how banks scale effects management alpha, the unobserved variable, however.

Time to Resolve Chapter 11

Company sales (log transformed) has a significant negative coefficient when regressing on dependent variable Time to Resolve Chapter 11 (log transformed). Companies with a greater ability to generate revenue experience a shorter trip through the Chapter 11 process.

There is a significant relationship between investment banking characteristics and the time to resolve bankruptcy at lag zero. The coefficient on the squared investment banking debt-to-asset ratio is positive and significant at 1% confidence, indicating that middle-leverage investment banks advise companies that take quick trips through Chapter 11. Likely, middle leverage banks take on low LTV Chapter 11 deals, and due to the lower risk profile of these companies, are able to more quickly move the company through bankruptcy. High and low leverage banks are likely

to take on higher LTV deals and thus experience long times spent in the bankruptcy process while the company is restructured.

VI. CONCLUSION

While corporate and economic features are significant in the total DIP financing procured, the DIP LTV, and time in bankruptcy, investment banking characteristics play an important role in the DIP loan-to-value. As banks scale up their overall size and investment banking arm, they have the capacity to take on higher LTV deals some years after these changes begin to take effect. The investment banking leverage ratio also impacts the time for the bank to complete deals. High and low leverage banks are likely to take on higher LTV deals and thus experience long times spent in the bankruptcy process while the company is restructured. Overall, the value that the investment bank provides is tenuous – opportunistic banks may engage in high LTV DIP deals in order to juice returns for the investment banking shareholders and to pay down their own debt. However, the advisory service that the investment bank provides at middle leverages can lead to quick times through the Chapter 11 process, and larger banks will undertake riskier deals given that they have headcount and large investment banking wings to fully diligence the deals.

VII. CITATIONS

- Adler, Barry E. “Game-Theoretic Bankruptcy Valuation.” *The Journal of Legal Studies*, vol. 41, no. 1, 2012, pp. 209–38. *JSTOR*, doi:10.1086/665705.
- Baird, Douglas G., and Robert K. Rasmussen. “Private Debt and the Missing Lever of Corporate Governance.” *U. Pa. L. Rev.*, vol. 154, 2005, p. 1209.
- Baird, Douglas, and Robert Rasmussen. “The End of Bankruptcy.” *JOHN M. OLIN LAW & ECONOMICS WORKING PAPER*,
<https://poseidon01.ssrn.com/delivery.php?ID=514112092086126112007008121094000026073010042041037058069127096101095123017011011007058100023094068097071090097058000012000017081006110011101113017114127027049081051078004127084072097083116078025106110064094021100002023031104073126094017103092&EXT=pdf>.
- Bolton, Patrick. “Toward a Statutory Approach to Sovereign Debt Restructuring: Lessons from Corporate Bankruptcy Practice around the World.” *IMF Staff Papers*, vol. 50, 2003, pp. 41–71. *JSTOR*.
- Bris, Arturo, et al. “The Costs of Bankruptcy: Chapter 7 Liquidation versus Chapter 11 Reorganization.” *The Journal of Finance*, vol. 61, no. 3, 2006, pp. 1253–303. *JSTOR*.
- Carapeto, Maria. *Does Debtor-in-Possession Financing Add Value?* SSRN Scholarly Paper, ID 161428, Social Science Research Network, 1 Apr. 1999. *papers.ssrn.com*,
<https://papers.ssrn.com/abstract=161428>.
- Chatterjee, Sris, et al. “Debtor-in-Possession Financing.” *Journal of Banking & Finance*, vol. 28, no. 12, Dec. 2004, pp. 3097–111. *ScienceDirect*, doi:10.1016/j.jbankfin.2004.05.003.

- Dahiya, Sandeep, et al. "Debtor-in-Possession Financing and Bankruptcy Resolution: Empirical Evidence." *Journal of Financial Economics*, vol. 69, no. 1, July 2003, pp. 259–80. *Crossref*, doi:10.1016/S0304-405X(03)00113-2.
- Dahiya, Sandeep, and Korok Ray. *A Theoretical Framework for Evaluating Debtor-in-Possession Financing*. SSRN Scholarly Paper, ID 2447868, Social Science Research Network, 9 June 2014. *papers.ssrn.com*, <https://papers.ssrn.com/abstract=2447868>.
- Demiroglu, Cem, and Christopher M. James. *Bank Loans and Troubled Debt Restructurings*. SSRN Scholarly Paper, ID 2336007, Social Science Research Network, 13 May 2015. *papers.ssrn.com*, <https://papers.ssrn.com/abstract=2336007>.
- Elayan, Fayez A., and Thomas O. Meyer. "The Impact of Receiving Debtor-in-Possession Financing on the Probability of Successful Emergence and Time Spent Under Chapter 11 Bankruptcy." *Journal of Business Finance & Accounting*, vol. 28, no. 7–8, Sept. 2001, pp. 905–42. *Wiley Online Library*, doi:10.1111/1468-5957.00398.
- Hasan, Iftekhhar, et al. "Lock-In Effects in Relationship Lending: Evidence from DIP Loans." *Journal of Money, Credit and Banking*, vol. 0, no. 0. *Wiley Online Library*, doi:10.1111/jmcb.12569.
- Ivashina, Victoria, et al. *The Ownership and Trading of Debt Claims in Chapter 11 Restructurings*. SSRN Scholarly Paper, ID 1573311, Social Science Research Network, 5 June 2015. *papers.ssrn.com*, <https://papers.ssrn.com/abstract=1573311>.
- Jackson, Thomas H., and David A. Skeel. *Bankruptcy and Economic Recovery*. SSRN Scholarly Paper, ID 2306138, Social Science Research Network, 1 July 2013. *papers.ssrn.com*, <https://papers.ssrn.com/abstract=2306138>.
- James, Christopher. "When Do Banks Take Equity in Debt Restructurings?" *The Review of Financial Studies*, vol. 8, no. 4, Oct. 1995, pp. 1209–34. *academic.oup.com*, doi:10.1093/rfs/8.4.1209.

Lopucki, Lynn. "The Debtor in Full Control--Systems Failure under Chapter 11 of the Bankruptcy Code." *American Bankruptcy Law Journal*, vol. 57, Jan. 1983.

Nigam, Nirjhar, and Afef Boughanmi. "Can Innovative Reforms and Practices Efficiently Resolve Financial Distress?" *Journal of Cleaner Production*, vol. 140, Jan. 2017, pp. 1860–71. *ScienceDirect*, doi:10.1016/j.jclepro.2016.09.190.

Rozens, Aleksandrs. "Corporate America's Transfusion." *Investment Dealers' Digest*, vol. 74, no. 41, Oct. 2008. Nexis Uni.

User's Manual.pdf.

Zumbro, Paul. "DIP and Exit Financing Trends and Strategies in a Changing Marketplace." *Recent Trends in Debtor-in-Possession Financing*, Aspatore, 2016, https://www.cravath.com/files/uploads/Documents/Publications/3616890_1.PDF.

VIII. APPENDIX

Table 1: Effect of Macroeconomic Conditions on DIP LTV and Total Days to Resolution

	DIP Loan Value to Assets (Risk)			log Total Days to Resolve Chp. 11		
	(1)	(2)	(3)	(4)	(5)	(6)
Prime Interest Rate	0.071 ^{***}	0.072 ^{**}	0.082 ^{***}	0.005	-0.006	-0.133
	(0.027)	(0.028)	(0.030)	(0.172)	(0.177)	(0.179)
GDP	-0.002	-0.003	-0.001	-0.037 ^{***}	-0.034 ^{**}	-0.057 ^{***}
	(0.002)	(0.002)	(0.002)	(0.012)	(0.014)	(0.014)
Median Oil Price		-0.0002			0.001	
		(0.001)			(0.004)	
End of Period Oil Price			0.001			-0.012 ^{**}
			(0.001)			(0.005)
Constant	0.132	0.166	-0.070	9.101 ^{***}	8.798 ^{***}	12.431 ^{***}
	(0.207)	(0.264)	(0.321)	(1.160)	(1.563)	(1.775)
Observations	112	112	112	155	155	155
R ²	0.064	0.064	0.069	0.068	0.069	0.104
Adjusted R ²	0.046	0.038	0.044	0.056	0.050	0.086
Residual Std. Error	0.133 (df = 109)	0.134 (df = 108)	0.133 (df = 108)	0.913 (df = 152)	0.915 (df = 151)	0.898 (df = 151)
F Statistic	3.698 ^{**} (df = 2; 109)	2.458 [*] (df = 3; 108)	2.685 [*] (df = 3; 108)	5.550 ^{***} (df = 2; 152)	3.705 ^{**} (df = 3; 151)	5.820 ^{***} (df = 3; 151)

Notes:

^{***}Significant at the 1 percent level.

^{**}Significant at the 5 percent level.

^{*}Significant at the 10 percent level.

Table 2: Effect of Company Conditions on DIP Sizing

	log Total DIP Loan Size					
	(1)	(2)	(3)	(4)	(5)	(6)
log Company Liabilities	0.660 ^{***} (0.068)		0.349 ^{***} (0.083)		0.331 ^{***} (0.083)	
log Company Assets		0.650 ^{***} (0.070)		0.328 ^{***} (0.082)		0.317 ^{***} (0.081)
log Company Sales			0.421 ^{***} (0.078)	0.445 ^{***} (0.076)	0.364 ^{***} (0.082)	0.377 ^{***} (0.081)
Company # Employees					0.00001 ^{**} (0.00000)	0.00001 ^{**} (0.00000)
Constant	0.064 (0.508)	0.147 (0.527)	-0.550 (0.467)	-0.561 (0.477)	-0.101 (0.511)	-0.092 (0.515)
Observations	112	112	112	112	112	112
R ²	0.465	0.438	0.578	0.572	0.593	0.591
Adjusted R ²	0.460	0.433	0.570	0.564	0.582	0.579
Residual Std. Error	1.024 (df = 110)	1.049 (df = 110)	0.913 (df = 109)	0.919 (df = 109)	0.901 (df = 108)	0.903 (df = 108)
F Statistic	95.480 ^{***} (df = 1; 110)	85.642 ^{***} (df = 1; 110)	74.575 ^{***} (df = 2; 109)	72.898 ^{***} (df = 2; 109)	52.511 ^{***} (df = 3; 108)	51.982 ^{***} (df = 3; 108)

Notes:

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table 3: Effect of Company Conditions on Bankruptcy Timing

	log Total Days to Receive DIP, 1-2		log Total Days to Resolve Chp. 11, 3-6			
	(1)	(2)	(3)	(4)	(5)	(6)
log Company Liabilities	0.880 ^{**} (0.386)		0.209 ^{***} (0.053)		0.132 [*] (0.072)	
log Company Liabilities (squared)	-0.051 ^{**} (0.024)					
log Company Assets		1.153 ^{***} (0.420)		0.222 ^{***} (0.054)		0.153 [*] (0.071)
log Company Assets (squared)		-0.068 ^{**} (0.026)				
log Company Sales					0.080 (0.071)	0.070 (0.070)
Company # Employees					0.00000 (0.00000)	0.00000 (0.00000)
Constant	0.063 (1.521)	-1.004 (1.631)	3.787 ^{***} (0.407)	3.697 ^{***} (0.410)	3.793 ^{***} (0.454)	3.705 ^{***} (0.455)
Observations	110	110	155	155	155	155
R ²	0.058	0.085	0.091	0.099	0.108	0.116
Adjusted R ²	0.041	0.068	0.085	0.093	0.091	0.098
Residual Std. Error	0.603 (df = 107)	0.594 (df = 107)	0.899 (df = 153)	0.895 (df = 153)	0.896 (df = 151)	0.892 (df = 151)
F Statistic	3.318 ^{**} (df = 2; 107)	4.964 ^{***} (df = 2; 107)	15.262 ^{***} (df = 1; 153)	16.779 ^{***} (df = 1; 153)	6.119 ^{***} (df = 3; 151)	6.587 ^{***} (df = 3; 151)

Notes:

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table 4: Total Model vs. All Dependent Variables [Lag 0]

	log Total DIP Financing Procured <i>OLS</i>		DIP Loan Value to Assets (Risk) <i>OLS</i>		log Total Days to Receive DIP <i>OLS</i>		log Total Days to Resolve Chp. 11 <i>OLS</i>		Chp. 11 Emergence <i>probit</i>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Prime Interest Rate	0.191 (0.191)	0.277 (0.229)	0.065** (0.025)	0.081*** (0.030)	-0.060 (0.135)	-0.098 (0.156)	-0.285* (0.166)	-0.343** (0.168)	-0.228 (0.271)	0.086 (0.325)
log Company Liabilities	0.337*** (0.084)	0.211* (0.121)	-0.050*** (0.011)	-0.066*** (0.016)	0.078 (0.062)	0.105 (0.084)	0.168** (0.072)	0.042 (0.081)	0.092 (0.126)	0.035 (0.162)
log Company Sales	0.351*** (0.086)	0.524*** (0.169)	0.033*** (0.011)	0.066*** (0.022)	0.021 (0.058)	-0.088 (0.113)	0.023 (0.074)	0.231** (0.103)	0.117 (0.118)	0.099 (0.200)
Company Employees	0.00001** (0.00000)	0.00001 (0.00000)	0.00000** (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)	-0.00001 (0.00001)	-0.00000 (0.00001)
IB Debt to Asset Ratio	-2.123 (3.356)	10.614 (11.695)	-0.626 (0.447)	0.292 (1.520)	0.544 (2.302)	-7.993 (7.796)	-4.971* (2.742)	-13.560*** (4.910)	4.008 (4.571)	16.835* (8.986)
IB Debt to Asset Ratio (squared)	1.297 (2.918)	-8.251 (8.595)	0.534 (0.388)	-0.162 (1.117)	-0.151 (2.004)	6.096 (5.735)	5.031** (2.405)	10.923*** (3.846)	-2.556 (4.054)	-12.054* (7.203)
IB Cash		-0.00004 (0.0001)		-0.00001 (0.00002)		0.0001 (0.0001)		0.0002* (0.0001)		-0.0002 (0.0002)
IB Percent Revenue from Advisory		0.441 (0.768)		0.103 (0.100)		-0.054 (0.510)		-0.921* (0.486)		1.933* (1.006)
IB Employees		0.00003 (0.0001)		0.00001 (0.00001)		-0.0001 (0.0001)		-0.0001** (0.0001)		0.0002 (0.0001)
Constant	0.063 (1.281)	-4.920 (4.497)	0.208 (0.171)	-0.336 (0.584)	2.943*** (0.896)	6.456** (2.990)	5.834*** (1.061)	9.273*** (1.877)	-1.091 (1.786)	-7.041** (3.529)
Observations	111	75	111	75	109	73	153	105	152	104
R ²	0.602	0.631	0.265	0.340	0.049	0.122	0.164	0.297		
Adjusted R ²	0.579	0.580	0.223	0.248	-0.007	-0.004	0.130	0.231		
Log Likelihood									-68.687	-40.220
Akaike Inf. Crit.									151.374	100.440

Residual Std. Error	0.905 (df = 104)	0.942 (df = 65)	0.120 (df = 104)	0.122 (df = 65)	0.616 (df = 102)	0.625 (df = 63)	0.881 (df = 146)	0.815 (df = 95)
F Statistic	26.256*** (df = 6; 104)	12.359*** (df = 9; 65)	6.265*** (df = 6; 104)	3.714*** (df = 9; 65)	0.878 (df = 6; 102)	0.970 (df = 9; 63)	4.783*** (df = 6; 146)	4.467*** (df = 9; 95)

Notes:

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table 5: Total Model vs. All Dependent Variables [Lag 1]

	log Total DIP Financing Procured <i>OLS</i>		DIP Loan Value to Assets (Risk) <i>OLS</i>		log Total Days to Receive DIP <i>OLS</i>		log Total Days to Resolve Chp. 11 <i>OLS</i>		Chp. 11 Emergence <i>probit</i>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Prime Interest Rate	0.172 (0.191)	0.274 (0.243)	0.061** (0.026)	0.078** (0.032)	-0.070 (0.135)	-0.093 (0.163)	-0.278 (0.168)	-0.268 (0.186)	-0.246 (0.283)	-0.024 (0.335)
log Company Liabilities	0.304*** (0.083)	0.201 (0.129)	-0.054*** (0.011)	-0.065*** (0.017)	0.098 (0.061)	0.080 (0.089)	0.149** (0.073)	0.023 (0.087)	0.113 (0.128)	0.098 (0.164)
log Company Sales	0.380*** (0.083)	0.539*** (0.181)	0.036*** (0.011)	0.066*** (0.024)	0.0002 (0.056)	-0.081 (0.119)	0.045 (0.073)	0.241** (0.108)	0.055 (0.115)	0.035 (0.202)
Company Employees	0.00001** (0.00000)	0.00001 (0.00000)	0.00000** (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)	-0.00001 (0.00001)	-0.00000 (0.00001)
IB Debt to Asset Ratio	-2.326 (2.143)	6.286 (7.292)	-0.316 (0.291)	0.364 (0.949)	-1.069 (1.461)	-2.247 (4.762)	-2.336 (1.637)	-9.298* (5.161)	1.926 (2.586)	10.506 (8.990)
IB Debt to Asset Ratio (squared)	1.297 (1.869)	-4.849 (5.246)	0.285 (0.254)	-0.204 (0.682)	1.239 (1.277)	1.878 (3.430)	2.559* (1.452)	7.538** (3.733)	-0.321 (2.375)	-7.489 (6.592)
IB Cash		-0.0001 (0.0001)		-0.00000 (0.00002)		0.0002** (0.0001)		0.0001 (0.0001)		-0.0001 (0.0002)
IB Percent Revenue from Advisory		0.710 (0.708)		0.063 (0.092)		-0.212 (0.462)		-0.824* (0.466)		1.133 (0.865)
IB Employees		0.00004 (0.0001)		0.00001 (0.00001)		-0.0001* (0.0001)		-0.0001* (0.0001)		0.0001 (0.0001)
Constant	0.278 (1.088)	-3.692 (3.118)	0.144 (0.148)	-0.337 (0.406)	3.358*** (0.778)	4.717** (2.052)	5.211*** (0.892)	7.648*** (2.161)	-0.399 (1.501)	-4.143 (3.826)
Observations	109	68	109	68	107	66	151	95	150	94
R ²	0.614	0.625	0.271	0.353	0.066	0.189	0.151	0.306		
Adjusted R ²	0.591	0.567	0.228	0.253	0.010	0.059	0.115	0.232		
Log Likelihood									-65.850	-37.024
Akaike Inf. Crit.									145.699	94.047

Residual Std. Error	0.888 (df = 102)	0.968 (df = 58)	0.121 (df = 102)	0.126 (df = 58)	0.604 (df = 100)	0.631 (df = 56)	0.894 (df = 144)	0.841 (df = 85)
F Statistic	26.998*** (df = 6; 102)	10.754*** (df = 9; 58)	6.305*** (df = 6; 102)	3.521*** (df = 9; 58)	1.179 (df = 6; 100)	1.454 (df = 9; 56)	4.258*** (df = 6; 144)	4.157*** (df = 9; 85)

Notes:

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Table 6: Total Model vs. All Dependent Variables [Lag 2]

	log Total DIP Financing Procured <i>OLS</i>		DIP Loan Value to Assets (Risk) <i>OLS</i>		log Total Days to Receive DIP <i>OLS</i>		log Total Days to Resolve Chp. 11 <i>OLS</i>		Chp. 11 Emergence <i>probit</i>	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Prime Interest Rate	0.252 (0.196)	0.147 (0.257)	0.065** (0.026)	0.073** (0.034)	-0.043 (0.138)	-0.092 (0.180)	-0.252 (0.173)	-0.261 (0.192)	-0.346 (0.289)	-0.119 (0.365)
log Company Liabilities	0.310*** (0.084)	0.141 (0.138)	-0.055*** (0.011)	-0.064*** (0.018)	0.092 (0.062)	0.039 (0.099)	0.137* (0.074)	-0.002 (0.093)	0.084 (0.126)	0.072 (0.177)
log Company Sales	0.382*** (0.083)	0.555*** (0.191)	0.037*** (0.011)	0.058** (0.025)	0.010 (0.057)	-0.084 (0.130)	0.065 (0.075)	0.278** (0.113)	0.023 (0.116)	-0.023 (0.209)
Company Employees	0.00001** (0.00000)	0.00001 (0.00000)	0.00000** (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00000)	0.00000 (0.00000)	-0.00000 (0.00000)	-0.00000 (0.00001)	-0.00000 (0.00001)
IB Debt to Asset Ratio	-0.473 (1.419)	-3.282 (6.043)	-0.192 (0.192)	0.042 (0.800)	-0.151 (0.971)	-0.134 (4.103)	-1.039 (1.085)	-3.406 (4.451)	-1.983 (1.869)	2.367 (7.948)
IB Debt to Asset Ratio (squared)	-0.169 (1.271)	1.359 (4.020)	0.163 (0.172)	-0.030 (0.532)	0.255 (0.871)	0.203 (2.729)	1.185 (1.001)	2.913 (2.951)	2.594 (1.777)	-1.023 (5.372)
IB Cash		-0.0001 (0.0002)		-0.00003 (0.00002)		0.0002 (0.0001)		0.0001 (0.0001)		-0.0001 (0.0002)
IB Percent Revenue from Advisory		1.156 (0.967)		0.216* (0.128)		0.338 (0.657)		-0.326 (0.566)		0.907 (1.026)
IB Employees		0.0001 (0.0001)		0.00003* (0.00002)		-0.0001 (0.0001)		-0.0001 (0.0001)		0.0002 (0.0002)
Constant	-0.575 (0.978)	0.379 (2.978)	0.106 (0.132)	-0.228 (0.394)	3.100*** (0.714)	4.253** (2.080)	4.832*** (0.840)	5.570** (2.163)	1.480 (1.427)	-0.831 (3.919)
Observations	109	63	109	63	107	61	149	88	148	87
R ²	0.609	0.634	0.269	0.376	0.048	0.166	0.134	0.300		
Adjusted R ²	0.586	0.572	0.226	0.271	-0.010	0.019	0.097	0.219		
Log Likelihood									-64.996	-35.307
Akaike Inf. Crit.									143.993	90.614

Residual Std. Error	0.894 (df = 102)	0.972 (df = 53)	0.121 (df = 102)	0.129 (df = 53)	0.610 (df = 100)	0.659 (df = 51)	0.907 (df = 142)	0.821 (df = 78)
F Statistic	26.462*** (df = 6; 102)	10.195*** (df = 9; 53)	6.249*** (df = 6; 102)	3.555*** (df = 9; 53)	0.832 (df = 6; 100)	1.128 (df = 9; 51)	3.650*** (df = 6; 142)	3.710*** (df = 9; 78)

Notes:

***Significant at the 1 percent level.

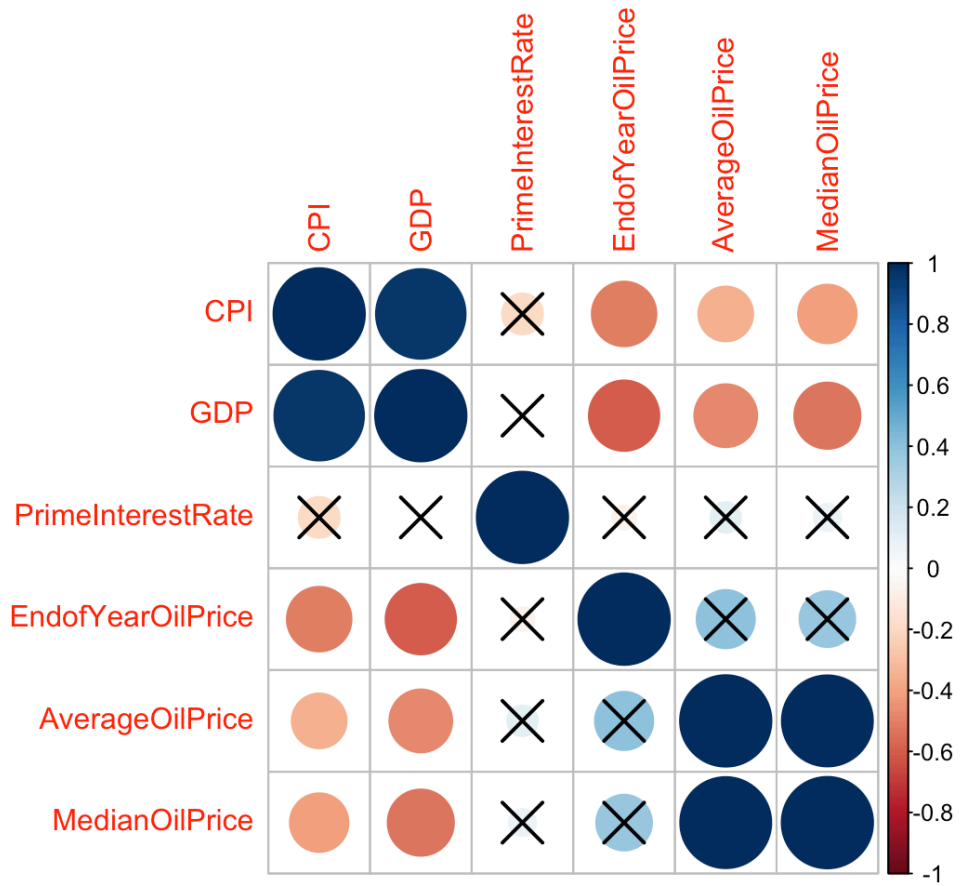
**Significant at the 5 percent level.

*Significant at the 10 percent level.

Figure 1: Summary Statistics of Key Independent Variables of Interest

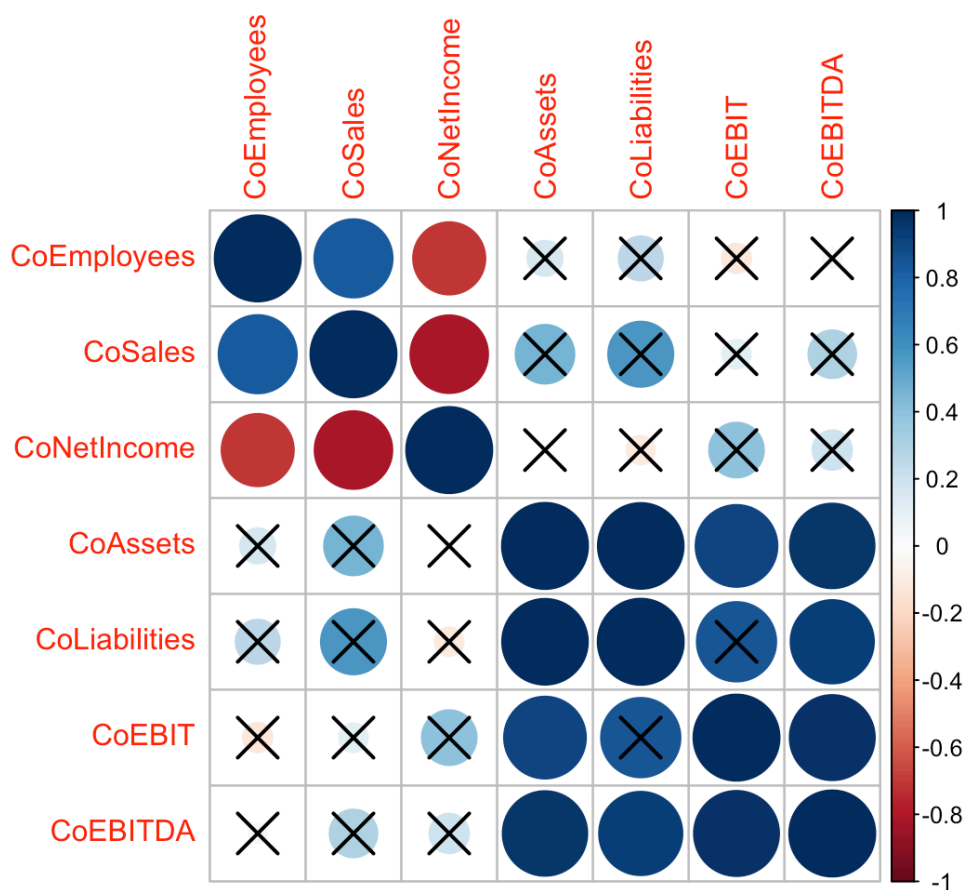
Statistic	US Consumer Price Index	GDP	Prime Interest Rate	Median Oil Price	Company Assets (log)	Company Liabilities (log)	Company # Employees (log)	Company Sales (log)	IB Debt to Asset Ratio	IB Cash	IB Percent Revenue from Advisory	IB # Employees
N	163	161	163	163	163	163	163	163	157	157	131	145
Mean	230.7	102.8	3.5	68.5	7.5	7.5	7.8	6.8	0.6	1,411.9	0.6	3,195.6
St. Dev.	12.4	6.8	0.5	20.7	1.3	1.4	1.7	1.5	0.2	1,433.0	0.3	3,052.1
Min	210.2	93.4	3.2	45.1	5.6	5.2	3.7	0.9	0.3	83.1	0.1	443.0
Pctl(25)	217.8	96.0	3.2	47.9	6.4	6.4	6.8	6.0	0.5	319.6	0.5	1,600.0
Pctl(75)	240.2	108.8	3.5	92.6	8.2	8.2	8.8	7.7	0.8	1,655.1	0.9	2,843.0
Max	252.9	115.2	6.0	104.8	13.4	13.4	12.4	11.9	0.9	7,535.3	1.0	14,647.0

Figure 2: Correlation of Macroeconomic Variables



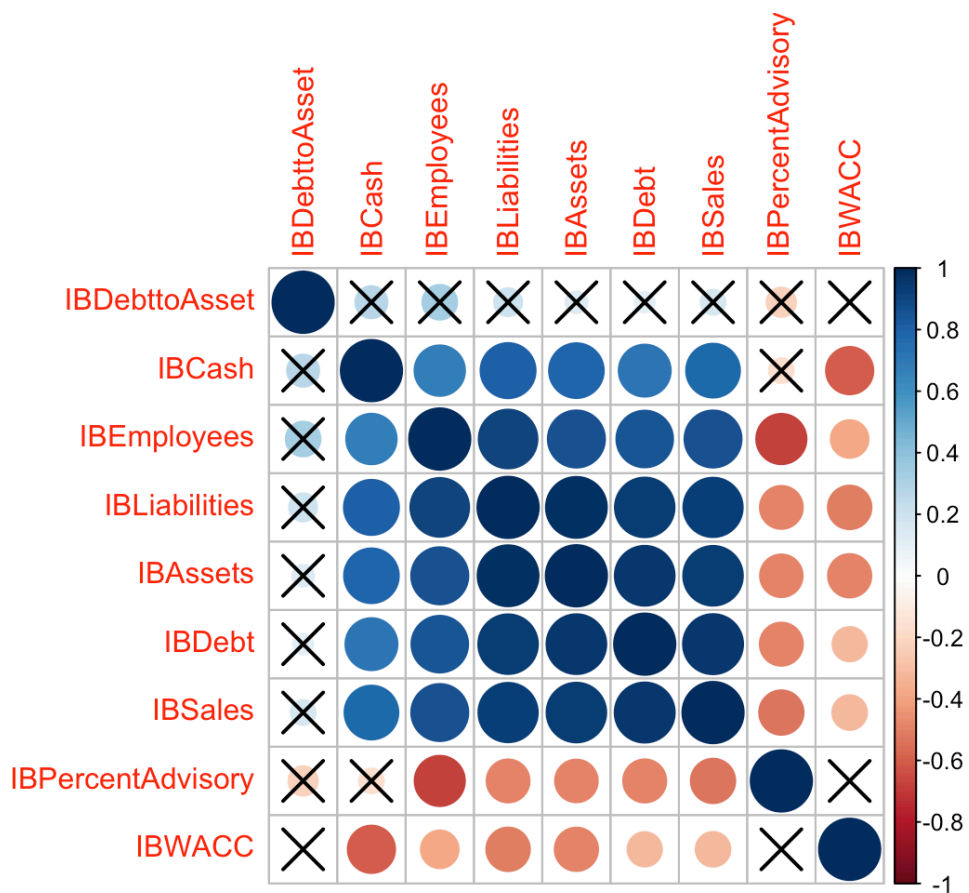
	CPI	GDP	PrimeInterestRate	AverageOilPrice	EndOfYearOilPrice	MedianOilPrice
CPI	1					
GDP	0.96	1				
PrimeInterestRate	-0.2	0	1			
AverageOilPrice	-0.36	-0.47	0.11	1		
EndOfYearOilPrice	-0.5	-0.59	-0.07	0.41	1	
MedianOilPrice	-0.41	-0.53	0.09	0.99	0.37	1

Figure 3: Correlation of Company Financial Characteristics



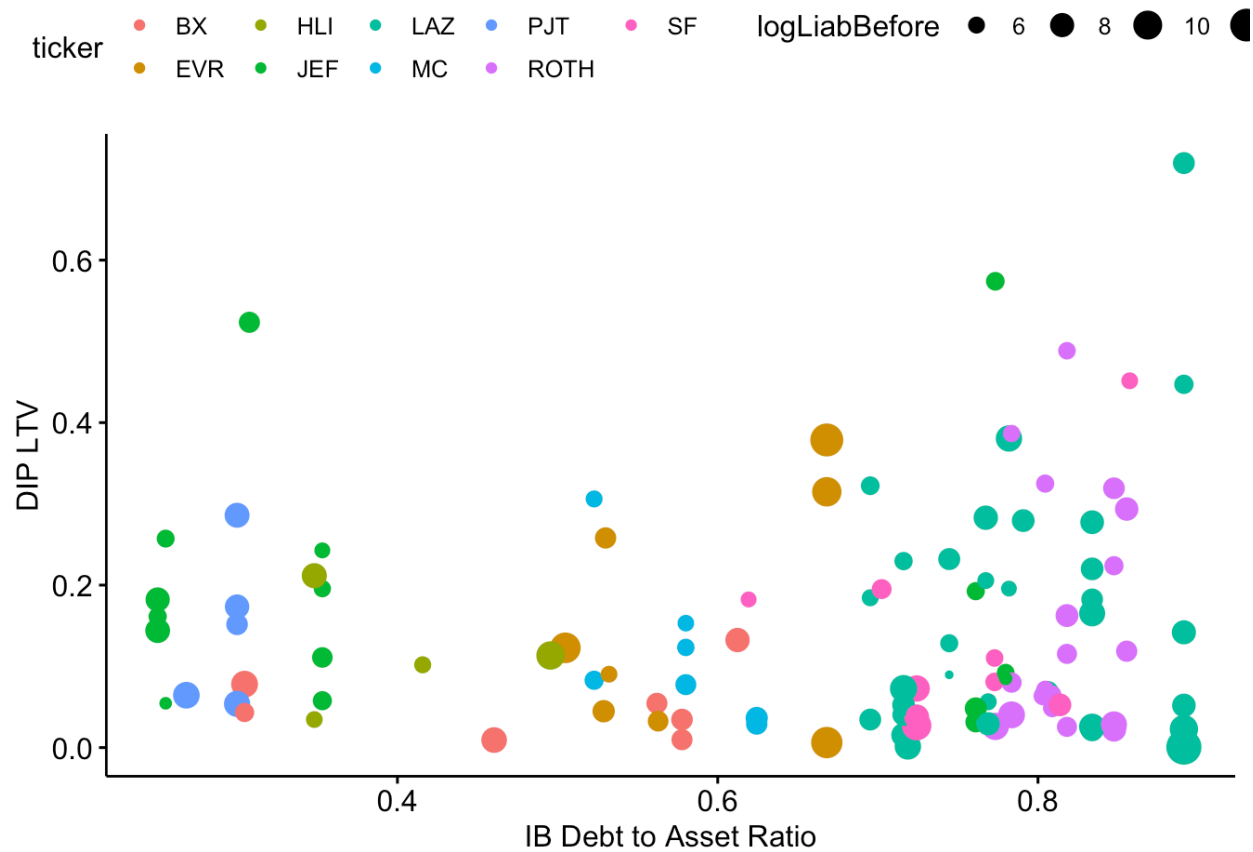
	CoAssets	CoEBIT	CoEBITDA	CoEmployees	CoNetIncome	CoLiabilities	CoSales
CoAssets	1						
CoEBIT	0.9	1					
CoEBITDA	0.97	0.98	1				
CoEmployees	0.17	-0.12	0.05	1			
CoNetIncome	0.01	0.4	0.21	-0.7	1		
CoLiabilities	0.99	0.85	0.94	0.26	-0.11	1	
CoSales	0.47	0.11	0.31	0.83	-0.81	0.57	1

Figure 4: Correlation of Investment Banking Characteristics



	IBDebt	IBLiabilities	IBCash	IBAssets	IBDebttoAsset	IBPercentAdvisory	IBWACC	IBSales	IBEmployees
IBDebt	1								
IBLiabilities	0.94	1							
IBCash	0.72	0.81	1						
IBAssets	0.95	0.99	0.8	1					
IBDebttoAsset	0.11	0.21	0.27	0.13	1				
IBPercentAdvisory	-0.49	-0.49	-0.16	-0.48	-0.23	1			
IBWACC	-0.31	-0.5	-0.6	-0.5	0	0.03	1		
IBSales	0.96	0.94	0.77	0.95	0.16	-0.52	-0.32	1	
IBEmployees	0.85	0.92	0.68	0.87	0.32	-0.67	-0.38	0.87	1

Graph 1: Scatter Plot of DIP LTV vs. Debt-to-Asset Ratio



Graph 2: Scatter Plot of Bankrupt Companies in Dataset, 2000-2018 (by Sector)

