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Private Equity Transaction Bankruptcy Risk Prediction

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PRIVATE EQUITY TRANSACTION BANKRUPTCY RISK PREDICTION

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ABSTRACT

This study utilizes a sample of private equity backed acquisitions to test whether certain factors, evaluated and quantified on the date of transaction completion, serve as indicators of future transaction bankruptcy. The results of this paper suggest that the effective federal funds rate is significantly and positively correlated with the bankruptcy of private equity backed transactions. Other measured factors specific to the private equity sponsor, the target firm in the acquisition and the characteristics of the transaction are found to be insignificant. Analysis on the influence of these factors is performed using two types of binary-response models, which predict the likelihood of the occurrence of bankruptcy, and a matched sample model that tests for the difference of means between a non-bankrupt transaction group and a bankrupt transaction group. Limitations in the availability of data derived from the private nature of the industry resulted in a limited sample size of 259 transactions completed from 1989 to 2008. General insignificance in the results of this study merits further analysis on the contributing factors to private equity transaction failure.

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1 INTRODUCTION

Zalmon G. Simmons revolutionized an industry and created an American business empire over one hundred and thirty years ago with the decision to mass-produce woven wire mattresses out of a small factory in Kenosha, Wisconsin, which resulted in the establishment of Simmons Bedding Company. The firm's subsequent reign over the bedding industry for over a century places Simmons in the same group with some of the oldest and most dominant firms in America's big-business history. Simmons was founded in 1870 during a period marked by rapid economic and population growth known as the "Gilded Age."[1] This era produced a number of dominant American manufacturing giants including Ford Motor Company, Standard Oil and United States Steel. While Simmons would likely not be in the running for a spot next to Ford on a list of America's greatest firms in history, most firms that have employed hundreds of thousands of Americans and have posted hundreds of millions of dollars in profit are recognized as quintessentially American.

In a history characterized by resilience and innovation, Simmons introduced the cotton felt mattress upon the conclusion of World War I, the studio couch (also known as the futon) as a low-cost alternative to the mattress during the Great Depression and king and queen sized mattresses in the late 1950s. Simmons later moved its headquarters to Atlanta, founded the Simmons Research Center to focus on product development, became the Official Bedding Supplier of the 1980 Winter Games in Lake Placid (Simmons Bedding Company, 2009) and was acquired in a

[1] Mark Twain and Charles Dudley Warner coined "Gilded Age" in their book *The Gilded Age: A Tale of Today* to refer to the extravagance and opulence of America's upper class during the post-Civil War Reconstruction era.

leveraged buyout (LBO) by prominent private equity firm Wesray Capital Corporation in 1986 for $120 million. After chopping up the company into distinct businesses and selling a number of them in order to pay back a portion of the capital that it had borrowed to finance the acquisition, Wesray sold Simmons to the second private equity group[2] in a string of five consecutive private equity backed deals[3] completed from 1986 to 2003. As sales and profits eroded during the recent economic downturn, Simmons was forced to file for corporate bankruptcy in 2009 under the Chapter 11 bankruptcy code of reorganization after defaulting on a scheduled interest payment on a portion of the firm's $1.3 billion in outstanding liabilities on its balance sheet (Creswell, 2009).

The fall of one of America's oldest and strongest companies under the management of Thomas H. Lee Partners (THL), an experienced sponsor in the private equity industry, did not go unnoticed in the financial press. According to Julie Creswell of The New York Times, the private equity sponsors involved in the string of LBO deals posted over $750 million in profits in the form of capital management fees,[4] incentive fees[5] and dividend recapitalizations[6] by acting as the general partners

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[2] The terms "private equity sponsor," "private equity group" and "private equity firm" are used interchangeably in this paper.

[3] A "private equity backed deal" occurs when a public or private investment firm acquires a firm in order to take an active role in the management of its operations.

[4] A "management fee" is the "percentage of the fund's net assets under management that is paid annually to fund management for administering the fund" (Ackermann, McEnally and Ravenscraft, 1999).

[5] An "incentive fee" is paid to the fund manager "only if the returns surpass some hurdle rate or 'high water mark' – meaning there is no incentive fee until the fund has recovered past losses" (Ackermann, McEnally and Ravenscraft, 1999).

[6] A 'dividend recapitalization,' also known as a 'leveraged recapitalization,' is the "process of borrowing money to issue a special dividend to owners or shareholders allowing them to recover a significant portion of their initial investment and make a substantial return in a buy-out very quickly" (Sousa, 2010).

(GPs) in limited liability partnerships (LLPs)[7] with investors that contribute capital to the sponsor's underlying private equity funds.[8] These underlying private equity funds lock up investor capital for a pre-specified investment horizon. At the end of a fund's investment horizon, the GP is required to close out of its position in all investments, i.e. sell its stake in all companies acquired during the lifetime of the fund. A private equity fund's relatively short investment horizon[9] and fee structure are brandished by Creswell to explain her characterization of Simmons's buyout history as "a Wall Street version of 'Flip This House.'" During the THL holding period, the private equity firm netted $77 million in profits even as one quarter of the firm's four thousand employees were laid off and the firm's debt load increased by over seventy percent from roughly $750 million to $1.3 billion as THL issued $375 million of additional debt to fund dividend recapitalizations. THL was unable to renegotiate the terms of the debt with the firm's creditors once Simmons's cash on hand became insufficient to service its upcoming interest payment and put the firm up for sale. With potential suitors concerned over the firm's highly levered capital structure, the offering proved unsuccessful and THL was forced to usher the firm into bankruptcy.[10] Refer to Figure 1 in the Appendix for a detailed illustration of Simmons's acquisition history and corresponding debt load since 1991.

[7] The structure of this arrangement allows investors to maintain "limited liability," i.e. responsibility only for contributed capital while the "general partner" acts as the manager of acquired firms and maintains unlimited liability.
[8] A private equity group typically has a "portfolio" of underlying private equity funds that operate independently in the acquisition of target firms.
[9] The average private equity fund's holding period is roughly six years (Kaplan and Strömberg, 2008).
[10] Simmons Bedding Company filed for bankruptcy with THL as its sponsor on November 16, 2009 and was acquired out of bankruptcy by Ares Management and Teachers' Private Capital on January 20, 2010 in a $760 million LBO transaction that reduced Simmons's debt load to $450 million.

Although the firm's road to failure, paved by private equity buyouts, is remarkable to recount, firm failure in the private equity industry is not entirely uncommon. Research on the demography of the industry estimates that roughly six percent (Strömberg, 2007) of all the private equity transactions completed from 1970 to 2007 are destined to fail. Julie Creswell and other critics of private equity argue that a transaction's failure can be traced back to the methods employed by the profit-driven sponsor to fund the acquisition such as an LBO or a dividend recapitalization, both of which involve the issuance of debt. On the other hand, industry proponents, including executives at THL, typically reject the idea that leverage contributes to a transaction's failure and point to the economic climate, industry vulnerability and other externalities as the contributing factors.

As is the case with most arguments, closer examination of the issue at hand can illuminate the validity in the rationale of each of the contrasting arguments. This provokes one to consider a host of other factors that may serve as indicators of future bankruptcy. This study takes an objective stance on this argument by analyzing a number of quantifiable factors upon the closing date of private equity acquisitions and the respective influence of these factors on transaction bankruptcy risk. A bankruptcy risk prediction model based on the fundamentals of predecessors such as Edward Altman's Z-Score and ZETA™ models and refined to specifically evaluate the private equity industry is synthesized to examine the myriad of potentially influential factors for each observation in a 259-transaction sample.

2 LITERATURE REVIEW

The private equity industry first became important to financial academics and the press during the private equity boom of the late 1980s, which is notorious for the leveraged buyout (LBO) acquisition. The financial press honed in on the excessive levels of debt used to acquire target firms and the employee layoffs and cost-cutting initiatives that typically follow. During economic expansions, the most debt-laden LBOs can be "financed with anywhere between 60 and 90 percent debt" (Kaplan and Strömberg, 2008), because the LBO's risk and reward profile that enables sponsors to achieve levered returns[11] calls for the sponsor to contribute some portion of the capital for the transaction as the creditor makes up the difference between the total transaction value and the sponsor's contributed equity. Transactions financed with extreme levels of debt typically occur during times of economic expansion because cheap credit is abundant and lending standards are low (Brunnermeier, 2009).

While the LBO is unquestionably the most popular method used by sponsors, acquisitions also occur in other forms including joint ventures, where multiple partners put up the equity to finance a transaction, and equity buyouts, where no debt is used to finance an acquisition. Those in favor of private equity acquisitions argue that the expertise of a private equity sponsor can be beneficial for the acquired firm when the sponsor cuts operating costs by reorganizing the firm's internal structure. Proponents also believe enhanced leverage "disciplines managers whose strategies are wasting resources" (Jensen, 1986), due to the high interest payments that the firm

[11] "Levered returns" are achieved when an investor pledges equity in conjunction with borrowing capital to purchase a financial asset. This strategy generates more volatility in the returns on the investment.

inherents post-acquisition. Opponents of the industry point to the acquired firm's reduced interest coverage ratio,[12] which is used to measure a firm's ability to service its interest, as detrimental to the firm's growth prospects because managers may not have enough cash available to invest in profitable projects.

This paper focuses on how quantitative factors and fundamental characteristics of the parties involved contribute to the bankruptcy risk of private equity backed transactions. The contributors that have been observed in previous literature include macroeconomic conditions, industry conditions and characteristics specific to the sponsor, target and transaction (Altman, Sabato and Nicholas, 2008). It is essential to weigh both the combined and individual effects of these contributors in order to construct a bankruptcy risk prediction model specific to the private equity industry.

The literature on failure prediction models originates with Altman's Z-Score model from 1968, which employs multiple discriminant analysis (MDA)[13] using five financial accounting ratios[14] in a model to evaluate the bankruptcy risk for public manufacturing corporations. Altman found the model to hold a predictive accuracy of 71.9% and 36.0% two years prior and five years prior, respectively, to the event of bankruptcy for firms during the sample period (Altman, 1968). Altman revisited the model in 1977 to develop the "second generation" ZETA™ model to reflect the "temporal nature of [bankruptcy] data." This model holds a predictive accuracy of

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[12] Interest coverage ratio = [Free Cash Flow / Interest Expense]

[13] "Multiple discriminant analysis" is a "unified approach [to] solving a research problem involving multivariate comparisons of several groups" using a number of explanatory variables (Tatsuoka and Tiedeman, 1954).

[14] Altman's financial accounting ratios include (i) Working Capital / Total Assets; (ii) Retained Earnings / Total Assets; (iii) EBIT / Total Assets; (iv) Market Value of Equity / Total Liabilities; and (v) Sales / Total Assets.

84.9% and 69.8% two years and five years prior to bankruptcy, respectively (Altman, Haldeman and Narayanan, 1977). Altman later adapts his models to evaluate both private firms and another for non-manufacturing firms (Altman, 2000). These developments in failure prediction models opened the door of opportunity by allowing for a host of different types of firms and transactions to be evaluated.

Shumway (2001) argues that static models[15] such as Altman's "are inappropriate for forecasting bankruptcy because… bankruptcy occurs infrequently [and] forecasters use samples that span several years to estimate their models." Shumway constructs a hazard rate model[16] that resolves the problem of evaluating data that is temporal in nature by explicitly accounting for time. Shumway attests that the improvement in the predictive power from Altman's Z-Score model to his ZETA model is founded on biased inferences that are inherent within the framework of static models. Hazard rate models account for these biases by controlling for each firm's period at risk, incorporating time-varying effects and also produce more efficient out-of-sample forecasts for the general population of firms by testing a larger sample within a longer observation period. Shumway's hazard rate model proved to have a statistically significant predictive accuracy of 86.4% two years prior to bankruptcy with a misclassification error of 2.4% as opposed to Altman's results of 77.6% and 8.8%, respectively. As is, Shumway's model cannot be adapted to measure the probability of failure for private firms, i.e. those lacking publicly

[15] A "static model" is one that evaluates the distribution of sample with specified parameters at a particular moment in time.

[16] A "hazard rate model" is a model that allows for the evaluation of independent hazard rates at different intervals.

available information, because Shumway depends on continuous firm-specific information flow to model bankruptcy risk probability movements over time.

Chava and Jarrow (2004) examine the merits of a private firm hazard rate model for the time period of 1962 to 1999 using the same construct as Shumway's model but "without the market variables and only using the accounting variables," as market data is neither available nor relevant for private firms. The researchers initially examine the predictive power of the bankruptcy hazard rate model for private firms using annual accounting data for which they find a predictive accuracy of 44.0% for a firm's future bankruptcy. The pair then examines a model using monthly accounting data and finds an increase in the predictive accuracy to 65.3%. This increase in predictive power with the use of shorter observation intervals allows the researchers to conclude that the timeliness of reported information is an important aspect of bankruptcy prediction accuracy. The predictive accuracy of this private firm hazard rate bankruptcy model is significantly lower than previous models that evaluated bankruptcy prediction for public firms, supporting the "notion of market efficiency with respect to publicly available accounting information" for failure prediction models. Unfortunately, the collection of monthly, quarterly or even annual data from the private equity industry is difficult, if not altogether impossible, which automatically reduces the theoretical effectiveness of a bankruptcy risk prediction model with a private equity focus.

Andrade and Kaplan (1998) argue for the inclusion of variables that measure macroeconomic and industry conditions in addition to firm-specific variables in their analysis on highly levered transactions. Included in these groups are variables that account for industry performance, firm performance within its industry, prevailing interest rates and the firm's relative interest expense within its industry. In addition, the researchers generate transaction-specific variables such as transaction debt to equity composition and dummies for the presence of junk bonds and the presence (and value) of bank debt in the LBO transaction. The formation of the variable groups in this study requires comprehensive information on all of the observations in order to construct a uniform data set. Generally, this information is difficult to come by for private equity transactions due to the clandestine nature of the industry's investment procedures.

The use of variables that analyze non-financial fundamentals in failure prediction models such as firm age, type of business, industrial sector, family ownership and auditor information, among others, has become prominent in recent years (Altman, Sabato and Nicholas, 2008). Wilson, Wright and Altanlar (2010) have found a number of these qualitative variables to exhibit statistical significance across the three major types of buyout transactions in the United Kingdom: the management buyout (MBO),[17] the management buy-in (MBI)[18] and the third-party private equity backed buyout. Some of the fundamental target-specific variables used in this study are dummies for family ownership, CEO or board member replacements and changes in a firm's auditor. To date, little research on the private equity industry focuses on how the presence of a private equity sponsor affects the financial health of the acquired firm. While the typical sponsor is largely motivated by profit, it also brings

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[17] A "management buyout" (MBO) usually involves a private equity acquisition in which the existing management takes a substantial proportion of the equity, which may be a majority stake in smaller transactions (Wilson, Wright and Altanlar, 2010).

[18] A "management buy-in" (MBI) is an MBO where the management team is composed of outsiders (Wilson, Wright and Altanlar, 2010).

a wealth of experience to the acquired firm, which allows the sponsor to act as an effective manager of operations.

The survey literature on this field has analyzed the demography of the private equity industry, fund investments, investment time horizons and the subsequent returns associated with these investments (Strömberg, 2007). Few have delved into the qualitative and quantitative attributes of a third-party private equity sponsor and the role these attributes may play in the eventual success or bankruptcy of the target firm. I propose that variables relating to the participation, decisions and qualities of a private equity fund are significant in the prediction of an acquired firm's bankruptcy. Research suggests the "odds of encountering financial distress or going bankrupt" are smaller when highly leveraged buyouts are sponsored by a third-party private equity group (Halpern, Kieschnick and Rotenberg, 2009).

This study will rely on "snapshot data," which is analogous to the type of data on a financial balance sheet, in order to analyze the predictive power of factors that have been observed and quantified on the date of a transaction's completion, as the nature of the industry prohibits continuous data collection. Accountants describe a balance sheet as a "snapshot" of the financial health of a company at a particular moment in time. This model aims to discover those factors that may serve as indicators of transaction failure by testing variables that have been designed to measure the impact of different forces on a transaction's eventual fate.

3 HYPOTHESIS

The data service that is most prominently used in this study is CapitalIQ, an online financial research service owned by Standard and Poor's that is used to analyze transactions by filling in data for a list of pre-determined variables. It is important to decide on these variables prior to using CapitalIQ's "transaction screening" tool because the generation of a uniform sample, i.e. one that contains a data point for every variable of concern for every observation, is necessary for the synthesis of a bankruptcy risk prediction model.

There are four variable groups of interest, each of which contains multiple underlying explanatory variables, whose contributions towards a transaction's eventual fate are tested. The first variable group measures the influence of macroeconomic conditions on a transaction's eventual bankruptcy. I hypothesize that poor macroeconomic conditions upon the date of the transaction result in lower of bankruptcy likelihood. The rationale behind this hypothesis is attributed to the more rigorous selection process that sponsors are required to take when selecting firms during times of economic hardship. While investor capital is usually locked up in private equity investments for a number of years by contractual obligation, incoming capital generally dries up during economic contractions, which forces firms to allocate resources more effectively by selecting the targets with the most profit potential. In order to do this, sponsors are theorized to work with additional caution during recessions and select firms that are better suited for a private equity backed acquisition.

The next two variable groups focus on the descriptive characteristics of private equity sponsors and their targets. The sponsor-specific group hypothesizes that transactions involving sponsors with less years of experience,[19] multiple sponsors[20] and public sponsors[21] will be more prone to bankruptcy than transactions backed by private equity firms whose characteristics fall on the opposite side of the spectrum. The target-specific group hypothesizes that public targets with more years of experience and operating within more stable industries[22] will be less prone to bankruptcy than younger firms that are private and operate within industries more sensitive to consumer demand preferences, e.g. the consumer discretionary products industry.

The final variable group analyzes transaction-specific data centered on the more empirical characteristics of a transaction. A number of dummy variables are used to examine the influence of different types of transactions on their eventual successes or failures. Included in this group are dummy variables for the presence of (i) an LBO; (ii) a secondary LBO;[23] (iii) a public to private transaction;[24] (iv) target management participation in the transaction; and (v) a dividend recapitalization. I hypothesize that bankruptcy risk will be higher for a transaction involving an LBO, secondary LBO or dividend recapitalization and lower for a transaction that is public to private or involves management participation.

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[19] "Years of experience" is calculated using the formula: [2010 *or* Bankruptcy Year – Founding Year].
[20] A private equity backed transaction can often involve multiple private equity sponsors.
[21] These are private equity sponsors that are traded on a public exchange.
[22] Measured by ranking industry inelasticity of demand," e.g. consumer staples industry is very inelastic.
[23] A "secondary LBO" is an LBO acquisition of a firm that has previously been acquired in an LBO.
[24] A "public to private" transaction occurs when a private equity sponsor buys a publicly-traded target firm and takes it private.

While all the variable groups may have underlying variables that hold explanatory power in the model, the variables in the sponsor-specific group and the transaction-specific group are of the most analytical importance in this study. These variable groups aim to examine the role of the sponsor, the financing decisions made by the sponsor, the managerial experience and the techniques that the sponsor brings to the table during the acquisition process.

4 DATA

4.1 Data Collection

The data collection process is extensive in the construction of a model to predict bankruptcy risk for private equity backed transactions. CapitalIQ, an online "comprehensive fundamental and quantitative" financial research service, is the primary source used to construct the sample. CapitalIQ's screening tool allows subscribed users to screen for data that fits into a specified set of parameters. The service has a database of specific information on a range of firms, transactions, investment vehicles and news that is generally unavailable elsewhere on the web. The parameters in my screening were set to render all closed merger and acquisition transactions backed by investment firms that have occurred in the United States since 1989 with total transaction values in excess of $150 million. While CapitalIQ allows us to gather information on transactions specifically backed by private equity sponsors, the screening tool does not have a filter for this parameter. The resulting sample contained a host of mergers and acquisitions conducted by all investment firms, including firms not classified as private equity sponsors. In addition, CapitalIQ does not allow screens to render information for a specified set of variables. Consequently, the generation of a dataset for the pre-specified variable list involves a labor-intensive process to weed out the observations that do not fit the above parameters or do not contain enough information to fill in data for each of the variables.

The screening parameters listed above were used as filters in the initial CapitalIQ screen, which rendered 2,326 unique transactions. Upon closer examination, it became apparent that a number of these observations did not qualify as private equity backed transactions or did not have enough data to use in a model whose creation is contingent on the ability to collect data for each of the variables for all of the observations within the sample. The contingencies and parameters imposed on the originally collected data caused roughly 88.9% of the original sample to be excluded from the baseline sample.

4.2 Data Filtration

<u>Exhibit 1</u>: Data Filtration Process

	Δ Sample	% Eliminated	New Sample	% of Original
Original Sample	2,326	0.0%	2,326	100.0%
Transaction Eliminations/Additions:				
Non private equity backed transactions	(1,810)	77.8%	516	22.2%
No "percent sought" information	(44)	1.9%	472	20.3%
No "buyer/seller" information	(24)	1.0%	448	19.3%
No "target date founded" information	(14)	0.6%	434	18.7%
No "consideration offered" information	(7)	0.3%	427	18.4%
No "transaction secondary features" information	(6)	0.3%	421	18.1%
No "deal resolution" information	(5)	0.2%	416	17.9%
REIT transactions	(112)	4.8%	304	13.1%
Transactions backed by hedge fund sponsors	(5)	0.2%	299	12.9%
Transactions with "percent sought" less than 61.0%	(11)	0.5%	288	12.4%
Transactions occuring post-2008	(29)	1.2%	259	11.1%
Sum/Remainder	**(2,067)**	**88.9%**	**259**	**11.1%**

The first step of the filtration process requires the identification of each of the 2,326 transactions as either "private equity backed" or "non private equity backed" in order to catch all mergers and acquisitions that are misclassified by CapitalIQ's screening tool. Approximately 77.8% (1,810 observations) of the sample rendered from the screen is eliminated in this filtration step, underscoring the weakness of observation misclassification when using a screening tool to gather data. The next step in the process discards all the observations without data for every variable in the pre-determined variable list by sorting through the sample to find transactions without information for (i) percentage sought; (ii) buyer/seller; (iii) target date founded; (iv) type of consideration[25] offered; (v) transaction features; or (vi) deal resolution. An additional 100 transactions (4.3% of the original sample) without data for the pre-determined variables were eliminated.

The filtration process then eliminates transactions misclassified as "private equity backed" in the first step by examining the sponsors and their targets more closely. Another 112 transactions (4.8% of the original sample) are found to have been backed by real estate investment trusts (REITs),[26] which are not private equity investment entities but rather investment vehicles that acquire properties and property portfolios. An additional 5 transactions (0.2% of the original sample) are excluded for being backed by hedge fund sponsors,[27] which differentiate themselves from private equity sponsors by seeking active investor roles as opposed to insider management roles. To further address this potential classification issue, another 11 transactions (0.5% of the original sample) are thrown out because the buyer acquired less than 61.0% of the target, suggesting investor activism as opposed to active management. Finally, 29 transactions (1.2% of the original sample) are eliminated for having occurred post-2008. This filtration excludes any transaction in its infancy,

[25] The "type of consideration" variable measures the type of collateral used to finance the acquisition of the target entity. A consideration can be offered in the form of cash, common equity or preferred equity, among many others.

[26] A "REIT" is "similar to a closed-end mutual fund [that] invest[s] in real estate or loans secured by real estate" (Bodie, Kane and Marcus, 2005).

[27] A "hedge fund" is a private investment pool… that is largely exempt from SEC regulation that can pursue more speculative [investments] than mutual funds (Bodie, Kane and Marcus, 2005).

i.e. younger than two years old, in order to give all transactions within the sample enough time to encounter financial or operating distress. The inclusion of young transactions could cause the data to become skewed because transactions doomed for failure are less likely to fail within a short time interval.

The remaining 259 transactions represent approximately 11.0% of the sample rendered from the initial screen. This "baseline sample" is evaluated throughout this paper to evaluate the effectiveness of a model that measures the effects of a number of regressors on the bankruptcy risk for private equity backed transactions. Each of the observations in the sample is chosen because it fits the criteria of being private equity backed and because information is available to collect data for each of the elected regressors that are grouped to explore the influences of sponsor, firm and target characteristics and the prevailing macroeconomic conditions on the probability of eventual target firm failure. Within the baseline sample, 18 transactions (6.9%) experience a future bankruptcy, closely mirroring results found by Strömberg (2007) and by Wilson, Wright and Altanlar (2010), in which 6.0 – 8.0% of all global private equity backed buyouts experience future bankruptcy. Refer to Figure 2 for an historical overview of private equity backed LBO bankruptcy rates.

5 RESULTS

5.1 Matched Sample Model

A matched sample of 33 bankrupt firms and 33 non-bankrupt firms was first utilized by Edward Altman to create his Z-Score model in 1968. As discussed in the literature review, all of these (public manufacturing) firms were matched by type of industry and approximate asset size. Considering Altman's relatively small sample size of 66 firms, the formation of an 18-transaction non-bankrupt group to match the 18 bankruptcies observed within the collected sample appears feasible. With the intent of replicating Altman's methodology, non-bankrupt transactions are paired with each of the 18 bankrupt transactions by transaction value and the target firm industry inelasticity ranking.[28] In his study, Altman restricts firm asset size range from \$1 to \$25 million to exclude smaller firms that do not release comprehensive financial information and also to exclude larger firms, which exhibited a low incidence of bankruptcy during the era. The framework of my study requires a lower bound on transaction size to exclude those smaller transactions that may skew the data but does not require the use of an upper bound on transaction values because not much is known about the relationship between transaction size and bankruptcy risk. A bankrupt group of 18 transactions and non-bankrupt group of 18 transactions are formed from the original sample of 259 to yield a matched sample of 36 private equity backed acquisitions that evaluates bankruptcy risk using the variable groups noted in the data section. Ideally, a transaction-specific variable for leverage would

[28] In this study, a target's industry inelasticity of demand is ranked on a scale of 1 – 9 (most elastic – most inelastic).

be synthesized in this model as the literature indicates that leverage is influential on the eventual outcomes of private equity backed transactions (Andrade and Kaplan, 1998).

After constructing this matched sample, it is necessary to run a difference of means t-test[29] to determine which variables, if any, contribute to the fate of a transaction as bankrupt or non-bankrupt. Individual t-tests on each variable are run to determine whether or not the means of the 19 explanatory variables from each group are different with any statistical significance. At the 5.0% significance level, the only variable whose group means are statistically different is the target firm industry inelasticity ranking. At the 10.0% significance level, the dummy variable for a secondary LBO transaction and the continuous variable for the target firm industry inelasticity ranking are the variable means that are statistically significant across the two groups. Statistical significance implies that these variables may affect the eventual fate of a transaction as bankrupt or non-bankrupt after a private equity backed acquisition occurs. Other notable results for the bankrupt and non-bankrupt group, respectively, include average transaction values of $815.6 million and $685.7 million, percentages of LBOs of 88.9% and 94.4%, percentages of secondary LBOs of 33.3% and 66.7% and percentages of the target sought by the sponsor of 96.9% and 100.0%. While the means of these variables do not exhibit statistically significant differences across groups, it is intriguing that the transactions from the bankrupt group (relative to the non-bankrupt group) are more likely to be higher in value, less likely to be LBOs or secondary LBOs and generally seek a smaller

[29] A "difference of means t-test" is a statistical approach used to test whether the means of two groups are different with statistical significance.

percentage of the target firm. Although the statistical significance of these results is negligible, the differences in the variable means between the two groups may partially capture the effect of leverage on firm performance, which could be positive, as the transactions in the bankrupt group are less likely to have been completed as LBOs or secondary LBOs. Leverage has been cited as one of the most important factors in a transaction's bankruptcy but, as mentioned previously, information on this data point for the baseline sample and was unavailable for the majority of observations. The means of the variables within the transaction-specific variable group, while statistically insignificant, highlight the importance of additional investigation on the influence of transaction leverage on failure. For a list of all summary statistics for the matched sample, please see Table 1 in the Appendix.

5.2 Binary-Response Models

It is necessary to analyze the entire 259-transaction baseline sample to derive the potential differentiating features between those 18 transactions doomed for failure and the remaining 241 that are destined to succeed. The self-evident weakness in evaluating a matched sample is the necessity to limit the number of non-bankrupt transactions in the control group to a number that matches the testing bankrupt group. We are prohibited from using MDA to analyze the baseline sample because the nature of our left-hand side bankruptcy variable is binary, i.e. non-continuous, and can only achieve a value of zero or one. In response to this issue, I use two types of multivariate binary-response models,[30] the logit model and the probit model, which predict the probability of the occurrence of an event, i.e. target bankruptcy. Both models estimate the joint probability of the occurrence of multiple correlated binary events with the assumption on the functional form of the relation between the dependent variable and the explanatory variables as the primary difference between the two models (Ashford and Sowden, 1970). The logit model assumes a cumulative logarithmic distribution while the probit model assumes a cumulative normal distribution to fit a functional shape onto the sample and calculate coefficients for the explanatory variables. When comparing the results from the models, the coefficients on our explanatory variables generally differ in magnitude but not in sign (positive or negative). The magnitudes of the coefficients capture the effect of the pre-determined distribution shape that each model assumes while the signs of the coefficients explain the relationship that each regressor has with the response variable. Refer to Table 4 in the Appendix for a full description of the regression coefficient results from the binary-response models.

The advantage of multivariate analysis over univariate analysis, which analyzes the independent relationships between the regressors and the response variable,[31] is the ability to observe the relationships that the explanatory variables share amongst each other. Often times, two or more variables within a set of explanatory variables are highly correlated, which can affect the signs and magnitudes of the coefficients for our variables and their significance. Of the original

[30] A "binary-response model" is a mean regression model in which the dependent variable takes only the values zero and one (Horowitz and Savin, 2001).
[31] The terms "response variable" and "dependent variable" are used interchangeable in this study to refer to the binary "bankruptcy" variable.

19 pre-determined regressors used in these models, the dummies for a cash consideration offered and the public status of a target fall victim to multicollinearity and are dropped from this analysis. Two more variables, the dummy for the presence of multiple sponsors and the continuous variable for number of sponsors involved in a transaction, contain data correlated with each other by over 70.0%, which requires the "number of sponsors" variable to be dropped from the models. Refer to Table 3 in the Appendix to view the complete correlation matrix for the pre-specified variable list.

The results from the binary-response models are also inconclusive, with only the effective federal funds rate variable used in the logit model exhibiting significance at the 10.0% level. As explained previously, this variable aims to capture the influence of macroeconomic conditions, specifically the cost of financing as determined by the Federal Bank, on a transaction's eventual success or failure. The resulting positive coefficient on the variable of [0.279] and the signs of the coefficients on the other macroeconomic variables[32] support the hypothesis that deals completed during times of economic expansion in which the Federal Bank typically raises interest rates to attract investor capital, are more prone to failure. The values of the coefficients on the variables in the remaining three variable groups, while statistically insignificant, point to the unexpected relationships between a number of regressors and the response variable.

The target-specific variable group holds mixed results if we compare the results to the hypothesized relationships between the two regressors within the group

[32] The other variables within this group are a dummy variable to measure whether a transaction occurs during an economic recession and a continuous variable to measure the magnitude of the TED Spread.

and the response variable. As hypothesized, results indicate that transactions involving older targets with more years of managerial experience are less prone to failure than those involving younger targets. Contrary to expectations, the positive coefficient on the variable ranking the inelasticity of demand of a target's industry suggests that targets operating within more inelastic, i.e. more stable, industries are less prone to failure than those operating in more volatile industries. The unexpected sign of the coefficient may have resulted from the arbitrary and somewhat subjective ranking process that I use to measure the relative resilience of a target's industry.

Coefficient results from the sponsor-specific variable group are entirely inconsistent with the hypothesized relationships between the regressors in the group and the dependent variable. These results suggest (i) transactions involving multiple sponsors are less prone to failure than those involving a single sponsor; (ii) acquisitions orchestrated by public sponsors are less prone to failure than those arranged by private sponsors; and (iii) buyouts completed by younger sponsors with less years of experience are less prone to failure than those consummated by older sponsors. The incongruity in the results relative to the hypotheses may be attributed to the potential existence of an incidental selection bias on the part of CapitalIQ towards the exclusion of less notable private equity deals arranged by younger sponsors that may have a higher bankruptcy incidence.

The majority of the relationships between the transaction-specific variables and the dependent bankruptcy variable in the results are also incongruent. The exceptions to this are the results for the dummy variable for a public-to-private transaction and the continuous variable for the sponsor's percentage sought in the target, which intimates that "going private"[33] transactions and transactions in which the sponsor acquires a high percentage of the target are less prone to failure than others. The coefficients on the remaining six variables within the transaction-specific group are inconsistent with the hypothesized relationships. Results propose (i) LBO transactions and secondary LBOs are less prone to failure than non-LBOs; (ii) public-to-private transactions are less prone to failure than other transactions; (iii) transactions completed without the participation of management are less prone to failure than those completed with management participation; and (iv) smaller transactions are less prone to failure than larger transactions. In the attempt to create a proxy for transaction leverage, I synthesized two variables by interacting the dummy LBO variable and the dummy secondary LBO variable with the continuous transaction value variable. These two variables were subsequently removed from the models upon the acknowledgement that the leverage ratio for a small buyout can be numerically identical to that of a large buyout.

The regression results from the binary-response models suggest that the prevailing macroeconomic conditions have a statistically significant influence on a transaction's eventual success or failure while the contributions from the remaining three variable groups are statistically insignificant. In addition, the binary-response models assume distributions that are likely not representative of the sample's actual distribution, as measured by the "pseudo R-squared." This descriptive statistic measures the goodness-of-fit of the functional form of a model by tabulating the percentage of the variation in the results explained by the regressors used in the model, which is 13.9% for the logit model and 14.17% for the probit model. This

[33] The terms "going private" and "public-to-private" are used interchangeable in this study.

study was designed to place greater analytical weight on the results from the sponsor-specific and transaction-specific variable groups over those from the macroeconomic-specific and target-specific groups. Statistically significant results from these groups would allow for analysis on the role of the sponsor, the financing decisions made by the sponsor and the deal experience and techniques that the sponsor brings to the table in the acquisition process. With results proving statistically insignificant for the two former groups, we cannot isolate and evaluate these factors with any certitude and have consequently reached the end of the road for analysis on this particular sample of transactions.

6 DISCUSSION

The principles of statistics and econometrics state that as the size of the studied sample increases, the mean and standard deviation of the sample approaches the true mean and standard deviation of the population. This axiom provides a potential explanation for the lack of significance in the results and could imply that the few variables found to be significant may not accurately represent the general population of private equity backed transactions with transaction values in excess of \$150 million. It is evident that the data collection process, which employs CapitalIQ's data screening tool, has adversely affected the quantity of observations contained within the baseline sample. For example, the sample contains only the transactions that have occurred since 1989 because CapitalIQ's database does not contain much data on the early history of private equity deals. The private equity industry is one that experiences waves of activity in which a multitude of transactions are completed during macroeconomic expansions. This limitation on the observation period leaves out the majority of transactions that occurred during the waves of private equity activity occurring prior to 1989, including the notorious LBO boom of the late 1980s. For an illustration on the distribution of transaction dates within the baseline sample, refer to Figure 3 in the Appendix.

The specificity of the research question, which limits the sample to third-party private equity backed transactions occurring in the United States with transaction values greater than \$150 million, also prohibits the collection of a larger sample size. MBOs, MBIs and third-party private equity backed transactions are used in Wilson, Wright and Altanlar's (2010) study on failure in the private equity industry in the

United Kingdom as opposed to solely examining third-party-backed transactions. The “type of investment firm” parameter is estimated to have limited the baseline sample size by two-thirds under the assumption that there exists an MBO and an MBI for each third-party private equity backed transaction within the industry. The “transaction size” parameter may be equally damaging to the size of my baseline sample because it excludes smaller transactions from the collected baseline sample. The literature attests that these excluded smaller private equity deals have a greater risk of bankruptcy, which suggests that the inclusion of smaller deals would not only have increased the size of the baseline sample but would have likely increased the incidence of bankruptcy within the sample (Wilson, Wright and Altanlar, 2010). If the assumption from the literature holds, the portion of bankrupt transactions within the baseline sample (6.9%) would have been larger had the excluded transactions with lower total values had been included. Refer to Figure 4 in the Appendix for an illustration of the baseline sample’s transaction value distribution.

CapitalIQ and the list of data parameters used in the data collection process may hold a selection bias and may have excluded bankrupt transactions that are (mis)classified as transactions completed by other types of investment firms. Strömberg and Kaplan (2008) utilize CapitalIQ’s screening tool to analyze the demography of the private equity industry and suggest the service “underreports private equity transactions before the mid-1990s, particularly smaller transactions.” These findings may contain a possible explanation as to why most of the transactions our sample occur post-1993 and why the average transaction size is as large as $783.6 million. The reason CapitalIQ underreports these types of transactions may be due to a bias towards the documentation of deals by more reputable and experienced sponsors, which are inherently less likely to encounter future failure as well (Wilson, Wright and Altanlar, 2010).

As noted previously, this study requires us to make use of snapshot data that is reported on the date of the target's acquisition to fill in variable data for a sample of transactions. Instead of using data from one date to predict a transaction's eventual bankruptcy, researchers prefer to use hazard rate models that utilize data from quarterly and annual reports. In the world of private equity investing where hundreds of millions of dollars of investor capital is often on the line, a "black box" period exists between the closed date of the transaction and the exit date of the sponsor's investment fund, during which most fundamental information relating to the performance of the target firm is sensitive, confidential and non-public. Even public sponsors, whose consolidated financials are required to be released on a quarterly basis, do not typically break out the performance of their subsidiary acquisition investments for fear of possibly compromising the returns on these investments and consequently losing out on future capital from investors that would not want to allocate capital to a fund if they knew that a subsidiary of the fund was performing poorly.

7 CONCLUSION

The results from the three economic models used in this study are inconclusive and generally inconsistent with the hypothesized relationships between the explanatory variables and the response variable for transaction bankruptcy. The matched sample model, which tests for significance in the difference in the means of the explanatory variables between the bankrupt and non-bankrupt groups, suggests a target's industry inelasticity of demand and the characterization of a transaction as an LBO are the only two influential factors on transaction bankruptcy. Results from the binary-response models validate the hypothesis that transactions are less likely to fail when the effective federal funds rate is lowered by the Fed in order to stimulate investment and consumption during macroeconomic contractions. With the exception of the federal funds rate variable, evidence from the binary-response models rejects the hypothesis that factors observed upon the date of a transaction's completion may serve as indicators of eventual transaction bankruptcy.

This paper takes a unique approach to financial distress within the American private equity industry with the construction of a bankruptcy risk prediction model reliant on data collected on the date of a deal's closing to predict its future bankruptcy. It is likely that the accuracy and effectiveness of the models are adversely affected by the private nature of the industry in question and the other limitations and weakness that have been acknowledged previously. It may well be the case that a model does not exist for the effective prediction of bankruptcy for private equity backed acquisitions. However, it is more likely that additional or unlimited access to data on the sponsors and their targets during the sponsor's holding period may bestow other researchers with the ability to more completely evaluate this topic.

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APPENDIX

Table 1: Matched Sample Model: *Summary Statistics*

	Variable Group	Means		Standard Deviations	
		Bankrupt	Non-Bankrupt	Bankrupt	Non-Bankrupt
Effective Federal Funds Rate**	Macroeconomic	4.63	3.38	1.65	2.55
TED Spread	Macroeconomic	0.67	0.73	0.42	0.56
Macroeconomic Contraction Dummy	Macroeconomic	0.06	0.22	0.24	0.43
Public Target Dummy	Target	0.00	0.06	0.00	0.24
Target Years of Experience	Target	38.00	48.33	40.75	46.50
No. Previous Transactions as Target	Target	3.17	2.67	1.34	1.24
Target Industry Inelasticity of Demand (1-9)*	Target	4.28	3.33	3.03	2.38
Public Sponsor Dummy	Sponsor	0.06	0.00	0.24	0.00
Sponsor Years of Experience	Sponsor	38.78	22.22	66.90	13.64
Multiple Sponsors Dummy	Sponsor	0.33	0.44	0.49	0.51
No. Transaction Sponsors	Sponsor	1.83	1.67	1.65	0.91
Total Transaction Value	Transaction	815.61	685.75	1,815.90	1,263.41
LBO Transaction Dummy	Transaction	0.89	0.94	0.32	0.24
Secondary LBO Transaction Dummy*	Transaction	0.33	0.67	0.49	0.49
Public-to-Private Transaction Dummy	Transaction	0.17	0.28	0.38	0.46
Management Participation Transaction Dummy	Transaction	0.28	0.44	0.46	0.51
Dividend Recapitalization Transaction Dummy	Transaction	0.11	0.17	0.32	0.38
Percentage of Target Sought	Transaction	0.97	1.00	0.08	0.00

*** Denotes statistical significance at the 5% level*

** Denotes statistical significance at the 10% level*

Total Observations: 36 (18 bankrupt, 18 non-bankrupt)

Table 2: Baseline Sample: *Summary Statistics*

	Variable Group	Mean	Standard Deviation	Minimum	Maximum
Bankruptcy Dummy	Response	0.07	0.25	0.00	1.00
Effective Federal Funds Rate	Macroeconomic	3.76	1.81	0.18	10.48
TED Spread	Macroeconomic	0.54	0.42	0.13	2.71
Macroeconomic Contraction Dummy	Macroeconomic	0.12	0.33	0.00	1.00
Public Target Dummy	Target	0.11	0.31	0.00	1.00
Target Years of Experience	Target	45.65	39.91	1.00	236.00
No. Previous Transactions as Target	Target	3.42	1.66	0.00	9.00
Target Industry Inelasticity of Demand (1-9)	Target	3.41	2.49	0.00	1.00
Public Sponsor Dummy	Sponsor	0.05	0.21	5.00	301.00
Sponsor Years of Experience	Sponsor	25.21	23.54	1.00	10.00
Multiple Sponsors Dummy	Sponsor	0.33	0.47	0.00	1.00
No. Transaction Sponsors	Sponsor	1.53	1.06	0.00	0.00
Total Transaction Value	Transaction	783.58	1,717.71	152.00	2,426.18
LBO Transaction Dummy	Transaction	0.95	0.23	0.00	1.00
Secondary LBO Transaction Dummy	Transaction	0.49	0.50	0.00	1.00
Public-to-Private Transaction Dummy	Transaction	0.22	0.42	0.00	1.00
Management Participation Transaction Dummy	Transaction	0.34	0.48	0.00	1.00
Dividend Recapitalization Transaction Dummy	Transaction	0.20	0.40	0.00	1.00
Percentage of Target Sought	Transaction	0.98	0.06	0.72	1.00

Total Observations: 259

Table 3: Baseline Sample: *Correlation Matrix*

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]
Bankruptcy Dummy [1]	1																		
Effective Federal Funds Rate [2]	0.13	1																	
TED Spread [3]	0.09	0.24	1																
Macroeconomic Contraction Dummy [4]	-0.05	-0.06	0.46	1															
Public Target Dummy [5]	-0.10	-0.16	-0.07	-0.01	1														
Target Years of Experience [6]	-0.05	0.03	0.02	-0.02	0.09	1													
No. Previous Transactions as Target [7]	-0.04	0.00	0.11	0.02	0.12	-0.06	1												
Target Industry Inelasticity of Demand (1-9) [8]	0.10	-0.03	0.08	0.03	0.15	-0.06	0.13	1											
Public Sponsor Dummy [9]	0.01	0.05	0.08	-0.02	0.10	0.07	0.08	-0.09	1										
Sponsor Years of Experience [10]	0.16	-0.03	0.12	0.08	0.00	-0.08	-0.04	0.12	0.07	1									
Multiple Sponsors Dummy [11]	0.00	0.00	-0.07	-0.06	-0.01	-0.02	0.01	-0.02	0.00	0.10	1								
No. Transaction Sponsors [12]	0.08	-0.03	-0.05	-0.04	-0.06	-0.04	0.01	-0.05	0.08	0.28	0.71	1							
Total Transaction Value [13]	0.01	-0.01	0.10	0.11	0.16	-0.04	-0.05	-0.11	0.06	0.00	0.11	0.02	1						
LBO Transaction Dummy [14]	-0.07	0.02	-0.04	0.04	0.08	0.05	-0.06	0.07	-0.43	-0.30	-0.27	-0.52	-0.02	1					
Secondary LBO Transaction Dummy [15]	-0.08	-0.11	-0.13	-0.12	0.11	0.12	0.16	0.10	-0.10	-0.05	-0.15	-0.03	-0.13	0.03	1				
Public-to-Private Transaction Dummy [16]	-0.04	0.10	0.23	0.23	-0.03	-0.10	0.07	-0.13	-0.03	-0.07	0.01	-0.04	0.19	0.04	-0.35	1			
Management Participation Transaction Dummy [17]	-0.04	-0.21	-0.22	-0.04	0.04	0.01	-0.05	-0.08	0.03	-0.05	0.13	0.09	-0.11	-0.01	0.16	-0.11	1		
Dividend Recapitalization Transaction Dummy [18]	-0.06	0.07	-0.10	-0.04	0.10	-0.09	0.19	0.07	0.03	0.00	0.18	0.12	-0.08	-0.01	-0.08	-0.13	0.00	1	
Percentage of Target Sought [19]	-0.03	-0.11	0.05	0.06	-0.10	-0.06	-0.10	-0.06	-0.10	0.04	0.06	0.03	0.06	-0.06	-0.04	0.18	0.12	-0.33	1

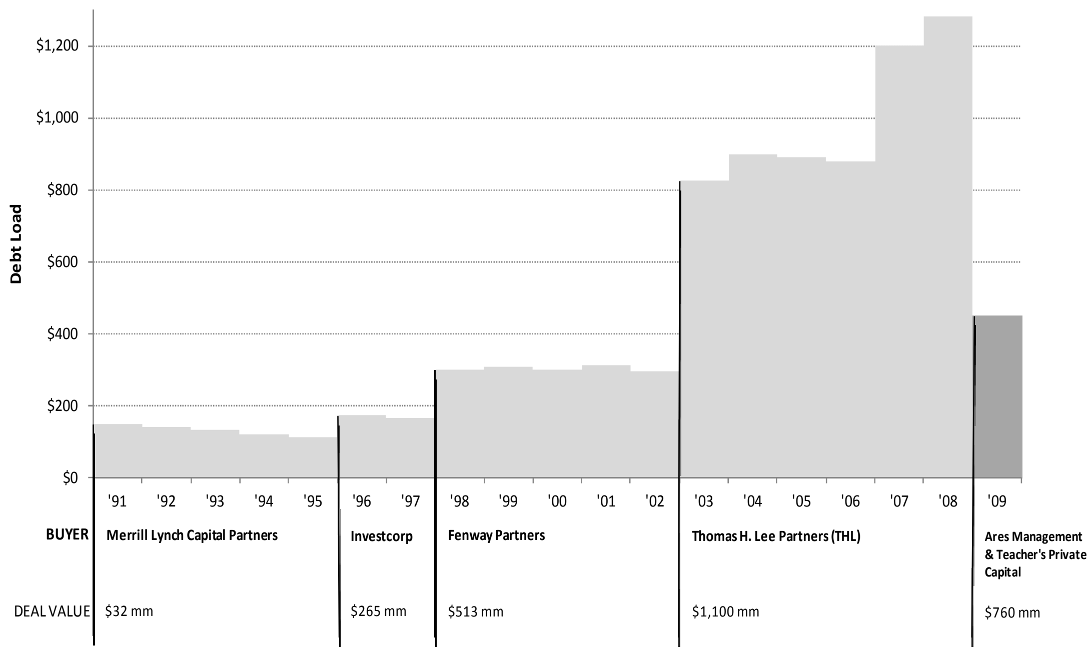
Table 4: Binary-Response Models: *Regression Results*

		Variable Coefficient	
	Variable Group	**Probit**	**Logit**
Effective Federal Funds Rate	Macroeconomic	0.1349	0.3081*
TED Spread	Macroeconomic	0.4694	0.9028
Macroeconomic Contraction Dummy	Macroeconomic	-0.8999	-1.6037
Public Target Dummy	Target	*Dropped*	
Target Years of Experience	Target	-0.0021	-0.0080
No. Previous Transactions as Target	Target	-0.0194	-0.0713
Target Industry Inelasticity of Demand (1-9)	Target	0.0875	0.1591
Public Sponsor Dummy	Sponsor	-0.2646	-0.7234
Sponsor Years of Experience	Sponsor	0.0051	0.0063
Multiple Sponsors Dummy	Sponsor	-0.2037	-0.3006
No. Transaction Sponsors	Sponsor	*Dropped*	
Total Transaction Value	Transaction	0.0001	0.0001
LBO Transaction Dummy	Transaction	-0.2200	-0.8035
Secondary LBO Transaction Dummy	Transaction	-0.4480	-0.9198
Public-to-Private Transaction Dummy	Transaction	-0.4372	-0.8712
Management Participation Transaction Dummy	Transaction	0.1996	0.2698
Dividend Recapitalization Transaction Dummy	Transaction	-0.6165	-1.2683
Percentage of Target Sought	Transaction	-2.6524	-3.5875

*** Denotes statistical significance at the 5% level*

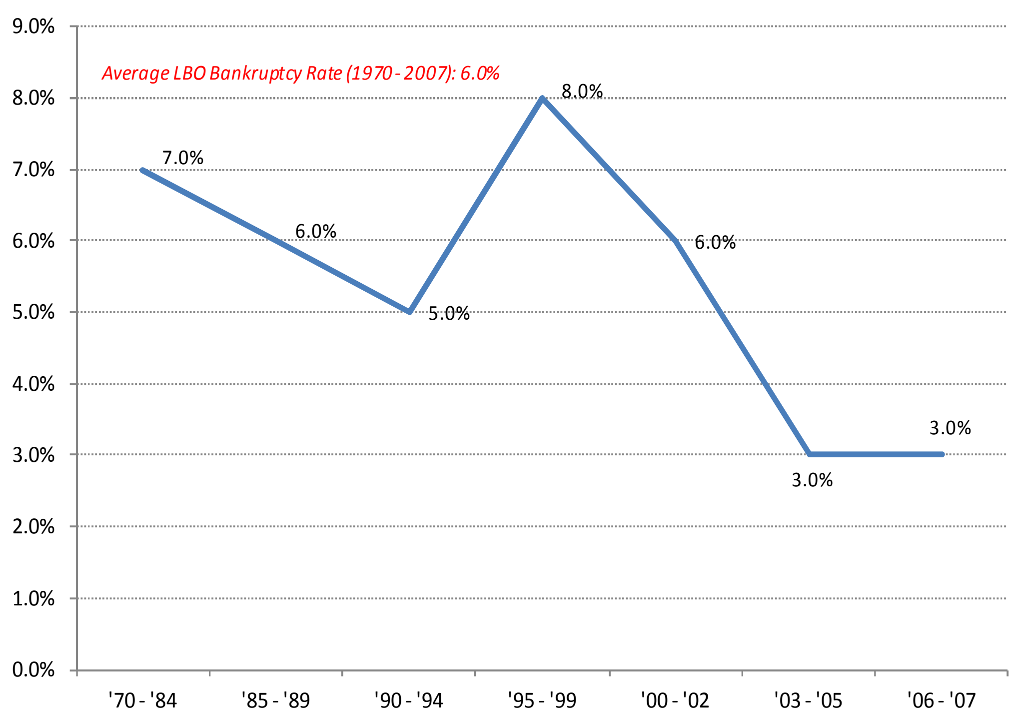
** Denotes statistical significance at the 10% level*

<u>Figure 1</u>: Simmons Bedding Company: *Transaction History*



Note: Simmons was acquired by Wesray Capital in 1986 and sold to the employee stock ownership plan in 1989.
Source: Creswell (2009)

<u>Figure 2</u>: Historical Bankruptcy Rate for Sponsor-Backed LBOs



Source: Strömberg (2007)

Figure 3: Baseline Sample: *Transaction Date Distribution*

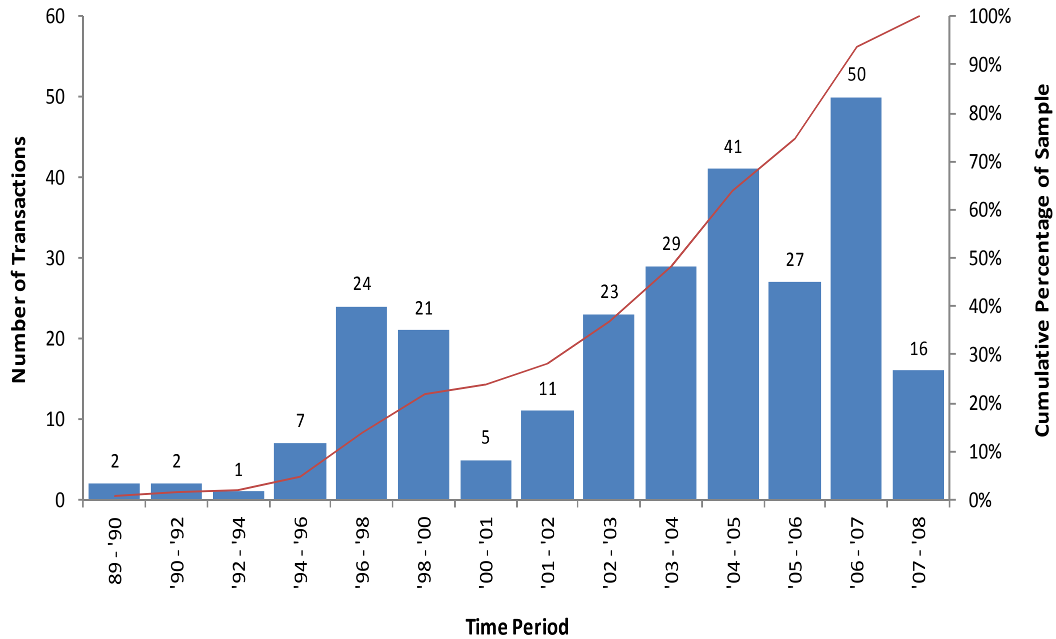


Figure 4: Baseline Sample: *Transaction Value Distribution*