WHY DO FIRMS FAIL, EMERGE, AND FAIL AGAIN? PREDICTING CORPORATE BANKRUPTCY WITH HAZARD MODELS

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ABSTRACT

This thesis examines the drivers of corporate distress for US-based, publicly-traded firms over the 1994-2018 period based on a dynamic logit model that was first applied for bankruptcy prediction by Shumway (2001) and later extended by Campbell et al (2008). Applying these techniques, we find that a vast majority of the variables of interest retained their underlying relationships with the probability of the first default, or Chapter 11. However, as we extrapolate these techniques to predicting repeated default, or Chapter 22, we discover that fundamental characteristics, such as profitability and leverage, play a considerably larger role than equity-market factors for reorganized firms. Finally, we extend both Shumway`s and Campbell`s specifications by incorporating macroeconomic and industry factors. We conclude that both are significant predictors of Chapter 11; in contrast, firms that remain distressed after being restructured tend to default irrespectively of the economic cycle.

Keywords: bankruptcy prediction, repeated bankruptcy, hazard model, economic cycle, industry effects

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CHAPTER 1. INTRODUCTION

While the ability to correctly estimate and price in the probability of corporate default has been of fundamental importance for every investor for over half-century, the 2008-2009 financial crisis showcased the necessity of updating existing risk management tools in the modern era of a rapidly changing financial landscape. This issue gains additional importance when we consider the fact that the U.S. economy is currently in its second longest period of expansion in history, which is currently1 one month away from breaking the record-high 120 months streak from March 1991 to March 2001.

In this thesis we revisit the best-in-class bankruptcy prediction models developed by Shumway (2001) and Campbell et al (2008) in order to estimate their explanatory power based on the most recent quarter-century of financial and economic data. Specifically, we use a dynamic logistic regression to estimate a time-discrete hazard model for predicting the probability of the initial corporate default over the 1994-2018 period based on a set of accounting and equity market-based variables for US-based, publicly-traded firms.

Further, we test if macroeconomic or industry factors also play an important role in predicting corporate default. To address the former, we experiment with a number of macroeconomic indicators by including them into both Shumway`s and Campbell`s specifications as a base of a hazard function; naturally, we expect the probability of default to be inversely related to the level of economic activity. In addressing the latter, we split the firms in our sample by industry into 10 categories using the Global Industry Classification Standard (GICS); we establish the "Industrials" sector as a base for comparison and test if there are any structural differences in the probability of facing financial distress among various sectors of the economy.

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[1] Federal Reserve Bank of St. Louis. Retrieved on May 30, 2019.

Finally, we hypothesize that the determinants of corporate default for reorganized firms are comparable to those of their healthy peers. We extrapolate both Shumway`s and Campbell`s models to predict repeated bankruptcy, and then optimize those models in order to arrive at their parsimonious versions. We also test for a potential improvement in the models` explanatory power from adding macroeconomic and industry factors.

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CHAPTER 2. RELATED RESEARCH

The foundation of modern empirical research on bankruptcy prediction was established by Beaver (1966), who was amongst the pioneers in using financial ratios for predicting corporate failure. By means of Univariate Discriminant Analysis, or “UDA”, he examined a sample of 79 healthy and 79 distressed companies and concluded that in contrast to their healthy peers, distressed companies tend to exhibit lower return on total assets and generate lower cash flow from operations to total assets.

The next building block in related research was laid down by Altman (1968). He argued that in predicting financial distress, examining individual financial signals in isolation from one another can lead to confusing results. In order to study those financial signals in groups, he applied the Multiple Discriminant Analysis technique, or “MDA”. Based on a sample of 33 healthy and 33 distressed firms, he found that simultaneous comparison of five financial ratios[2] tend to provide a reliable empirical framework for predicting corporate failure. The resulting model was later called “Altman Z-score” and has been extensively used by industry practitioners and scholars for years.

Despite wide recognition, subsequent research has identified several significant limitations of the Z-score model imposed by MDA. As indicated by Ohlson (1980) and Zmijewski (1984), this technique requires the variance-covariance matrices of the predictors to be the same for healthy and distressed firms, which leads to biased results due to oversampling troubled companies. Further, MDA assumes that all independent variables are normally distributed. Provided that logistic regression does not rely on the aforementioned distribution assumptions,

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[2] X1: Working Capital to Total Assets, X2: Retained Earnings to Total Assets, X3: EBIT to Total Assets, X4: Market Value of Equity to Total Debt, X5: Sales to Total Assets.

Ohlson (1980) developed a static logit model as an alternative to Altman Z-Score. Please see Ohlson (1980) for further details.

The next advancement in the empirical bankruptcy prediction methodology was related to an introduction of the dynamic logit model by Shumway (2001); he argued that static models are prone to producing biased and inconsistent results as they fail to capture trends in independent variables. Further, as an additional benefit to this technique, he pointed out that dynamic modelling naturally produces more efficient results as it relies on panel rather than cross-sectional data. Based on an extensive sample which included 300 bankruptcies over the 1962-1992 period, he found that several equity market-based factors have strong ties with the probability of corporate default, while approximately half of the financial ratios suggested by previous research were statistically insignificant. Shumway`s model was later adopted by Campbell et al (2008), who then introduced three additional variables, as well as adjusted the traditional accounting ratios for the market value of total assets. As a result, Campbell achieved a considerable improvement in the model`s explanatory power.

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CHAPTER 3. DATA DESCRIPTION

3.1 Dataset

In order to construct the dependent variable, the indicator of financial distress, we employ methodology which was initially developed by Chava and Jarrow (2004) and later used by Campbell, Hilscher and Szilagyi (2008): we define "financial distress" as an event of filing for bankruptcy under either Chapter 7 ("Liquidation") or Chapter 11 ("Reorganization") under the US Bankruptcy Code[3]; we then set the indicator at one in a calendar quarter when a filing occurs, and zero otherwise. This applies to both the first and any following bankruptcy filings.

Our primary source of bankruptcy information is Standard & Poor`s CapitalIQ®; the sample includes panel data for 10,418 publicly-traded US-based companies for the period from January 1994 until December 2018. The dataset includes all industry groups except those companies that are categorized as "Financials" by S&P`s Global Industry Classification Standards (GICS)[4]; the latter are excluded from the sample as their operating performance evaluation and governing bankruptcy law differ materially from the general industries (Shumway 2001).

Overall, there are 923 bankruptcy events in the sample: 890 out of 10,418 firms have filed for bankruptcy at least once over the period of interest; 22 of those who filed for bankruptcy once, have also had at least one subsequent filing, a so-called "Chapter 22".

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[3] Note that for simplification purposes we generally refer to the initial bankruptcy filing (either Chapter 7 or Chapter 11) as "Chapter 11" and to the subsequent filings as "Chapter 22" unless explicitly stated otherwise.
[4] Banks (GICS 4010), Diversified Financials (4020) and Insurance (4030).

Further, one company actually had the third filing within the 25-year time frame, which we treat as a separate Chapter 22 event. Note that we exclude six Chapter 22 events which occurred within 12 months from the preceding Chapter 11 as we view those cases as a single bankruptcy event[5]. Table 1 summarizes the properties of the dependent variable.

Table 1 – *Chapter 11s and 22s breakdown by year*

Year	Number of Bankruptcy Events	% of Total	Number of Chapter 22s	Number of Active Firms	Bankruptcy Rate
1994	2	0.20%	-	566	0.35%
1995	5	0.50%	-	1237	0.40%
1996	6	0.70%	-	2149	0.28%
1997	13	1.40%	-	2781	0.47%
1998	22	2.40%	-	3058	0.72%
1999	18	2.00%	-	3084	0.58%
2000	41	4.50%	-	3143	1.30%
2001	82	9.00%	1	3264	2.51%
2002	65	7.10%	1	3205	2.03%
2003	72	7.90%	2	3170	2.27%
2004	39	4.30%	1	3169	1.23%
2005	34	3.70%	1	3207	1.06%
2006	25	2.70%	-	3309	0.76%
2007	37	4.10%	1	3446	1.07%
2008	69	7.60%	2	3550	1.94%
2009	79	8.70%	3	3597	2.20%
2010	30	3.30%	1	3713	0.81%
2011	40	4.40%	2	3788	1.06%
2012	42	4.60%	-	3701	1.13%
2013	30	3.30%	1	3673	0.82%
2014	25	2.70%	2	3862	0.65%
2015	32	3.50%	-	3925	0.82%
2016	46	5.00%	2	3928	1.17%
2017	36	3.90%	1	3973	0.91%
2018	23	2.50%	2	3517	0.65%
Total	**913**	**100.00%**	**23**		

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[5] Generally, repeated filings within such a short time frame are driven by a dismissal of the initial petition by the court due to administrative or processual violations by the company.

Due to absence of any data in the CapitalIQ database prior to 1987 and significant limitations in bankruptcy and accounting data availability prior to Jan 1994, we exclude the 1987 – 1993 period from our sample. We also note that some of the aforementioned limitations are still observable up until Jan 2000: based on the Computstat database, Campbell et al reported 49 bankruptcy filings in 1998 and 30 filings in 1994 versus 22 and 2 in our sample, respectively. However, by 2000 the number of bankruptcies was broadly in line with other respectable databases (43 filings in 2000 as per the NYU Salomon Center Bankruptcy List versus 41 in our sample).

There are two key take-away points from Table 1. First, we observe 2 spikes in both the number of bankruptcies and bankruptcy rates in 2000-2001 and 2008-2009, which correspond to the dot-com bubble burst and the world financial crisis, respectively. Second, with exceptions for 2009 and 2016[6], the number of bankruptcies is generally trending down, while the number of companies in the sample is trending up. The latter dynamics partially contradicts actual trends in the number of publicly traded companies in the US. Specifically, Bloomberg reports a 47.1% drop (to 3,729) in the number of publicly-listed companies in the US over the 2000-2018 period and argues that among the primary reasons behind this decline were industry consolidation and stricter regulatory oversight of public companies in the post-Enron era.

There are two primary drivers behind this discrepancy. On the one hand, a gradual digitalization in the broad sense and in the field of financial reporting in particular, which took place since late 1990s, enabled various intelligence platforms like CapitalIQ to gather larger amounts of data more efficiently. On the other hand, successful platforms have been gaining scale and additional resources both organically and through acquiring competitors to increase their coverage, hence their inclusion ratios[7] have been gradually improving over time. Finally, we

[6] The largest oil prices drop since the September 2001 terrorist attacks in the US.
[7] Percentage of the companies covered by the data provider relative to the whole population.

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acknowledge that CapitalIQ is primarily used for decision-making in the fields of investment banking and financial advisory; hence it primarily concentrates on expanding its current event and accounting coverage rather than eliminating historical gaps in data[8]. While this approach eliminates the possibility of a survivorship bias in our sample, we have no reasons to believe there are other major systemic issues stemming from how our bankruptcy data was gathered.

In constructing our set of independent variables we primarily rely on methodology developed by Campbell et al (2008); quarterly accounting and equity market data is extracted from S&P`s CapitalIQ and Thomson Reuters Eikon databases, and our sole source of macroeconomic data is the Federal Reserve Economic Database. For simplicity, we divide all independent variables into the following categories.

The first category includes two accounting variables that were first used in dynamic bankruptcy modelling by Shumway (2001) and then by Chawa and Jarrow (2004): a ratio of book value of total liabilities to book value of total assets ("TLTA") as a measure capturing a firm`s leverage, and a ratio of net income to book value of total assets ("NITA") for profitability. We then winsorized both ratios at 1% and 99% levels to minimize the effect of outliers.

The second category consists of "hybrid" metrics, which are a combination of book and equity market variables initially developed by Campbell et al (2008). Following their approach, we first construct a hybrid measure of profitability via dividing net income by a sum of book value of total liabilities and market value of equity as of the last trading day of the respective quarter ("NIMTA"). The authors suggest that market-adjusted measures have stronger explanatory power given that market generally reacts more rapidly to changes in the firm`s prospects than once every quarter, and better estimates the true value of the firm`s intangible assets. We then construct a hybrid leverage metric ("TLMTA") in a similar manner. Finally, we add two more

[8] https://www.spglobal.com/marketintelligence/en/solutions/fundamental-data.

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measures: one capturing the firm`s immediate liquidity via dividing book value of cash and cash equivalents held on balance sheet by market-adjusted value of total assets (“CMTA”), and one for estimating the market`s sentiment towards company`s stock, a ratio of market-to-book value of equity (“MB”).

At this point, Campbell et al implement the following procedure in order to eliminate outliers driven by data quality issues: they add 10% of the difference between market and book equity to the book value of total assets and to the book value of equity. After completing this procedure, they report that some of the firm-months in their sample still have negative book value of equity, and they replace these negative values with small positive values of $1 to “ensure that the market-to-book ratios for these firms are in the right tail, not the left tail, of the distribution”. The authors then winsorize all independent variables at the 5^{th} and 95^{th} percentiles.

While we also observe some outliers in our sample, after an extensive testing we reached a conclusion that in our case following the “5-95” approach leads to an unnecessary loss of data and has no significant advantages compared to winsorizing at the 1^{st} and 99^{th} percentiles. Further, we argue that eliminating negative book value of equity via the aforementioned data manipulations is likely to distort important economic relationships between the market-to-book ratio, profitability metrics and the probability of default: companies that continuously generate negative net income usually accumulate negative retained earnings on their balance sheets, which in turn drags the firm`s book value of equity in the negative domain. Hence, we do not perform the aforementioned exercise in our sample; we winsorize all variables using the “1-99” approach.

The third category consists of pure equity market-based variables. Following the approach developed by Shumway (2001), we begin by constructing the relative size metric (“RSIZE”)

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by taking the log of the ratio of the firm`s share price to the value of S&P500 Index at the last trading day of each quarter. We then extract the firm`s daily stock price standard deviation over 3 months periods which are aligned with the firm`s respective fiscal quarters ("SIGMA"). Also, we construct the excess return metric ("EXRET") by taking the difference between logs of the firm`s quarterly return relative to the return of S&P 500 index. Finally, we calculate the change in firm`s share price via taking the log price per share truncated at $15 ("PRICE"): as per Campbell et al (2008), "this captures a tendency for distressed firms to trade at low prices per share, without reverse-splitting to bring price per share back into a more normal range".

The fourth factor we control for should capture changes in general economic environment. Existing literature suggests that adverse economic conditions are generally associated with higher probability of corporate bankruptcy (Chen 2010). However, different authors prefer different proxies to incorporate the macroeconomic factor into their models, such as changes in interest rate (Hillegeist 2004), prime rate[9] (Hill et al 2011) or other factors.

However, in this thesis we choose to employ Moody's seasoned Baa corporate credit spread[10], which is found to be a reliable leading indicator of real economic activity (see Mody and Taylor 2003, Gilchrist and Zakrajsek 2010) and in our view, has closer ties with corporate bankruptcy compared to general macroeconomic indicators like GDP or unemployment rate as it also captures the fundamental relationship between the cost of corporate debt and the firm`s ability to refinance its obligations on the one hand, and the probability of default on the other. In order to confirm this hypothesis, we test the performance of several macroeconomic variables including a percentage change in real GDP growth, a percentage points change in the FED rate, and the credit spread. We report our findings in the "Results and Discussion" section.

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[9] The lowest rate of interest at which money may be borrowed commercially.
[10] This metric reflects the spread between the Baa-rated corporate bond yield and the FED rate; it is measured in percentage points.

The final category of independent variables comprises a set of 10 industry dummies; we segregate firms into specific industry segments by their respective GICS codes. Please see the summary of the independent covariates in Table 2.

Table 2 - *Summary and definitions of independent variables*

Variable	**Definition**
Accounting-Based Variables	
NITA	Net Income / Book Value of Total Assets
TLTA	Total Liabilities / Book Value of Total Assets
Hybrid Variables	
NIMTA	Net Income / Market Value of Total Assets
TLMTA	Total Liabilities / Market Value of Total Assets
CMTA	Cash and Cash Equivalents / Market Value of Total Assets
Equity Market-Based Variables	
EXRET	*log* (1 + Quarterly Return on Firm`s Share) - *log* (1 + Quarterly Return on S&P 500)
RSIZE	*log* (Firm Market Value of Equity / Value of the S&P 500 Index)
SIGMA	3-months Average Standard Deviation of Daily Stock Returns
PRICE	*log* (Firm Market Value of Equity, per share)
MB	Market Capitalization / Book Value of Equity
Macroeconomic Variables	
MSPRD	Moody`s Baa Corporate Credit Spread
Industry Factor	
IND (1-10)	Set of Industry Dummies

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3.2 Descriptive Statistics

The entire dataset consists of 10,418 companies across 100 quarters which is equivalent to 25 years; we then segregate the sample into two groups. The pre-bankruptcy group[11] includes all firm-quarters prior to the first event of default (Chapter 11), if applicable; all available firm-quarters subsequent to Chapter 11 form the post-bankruptcy group.

Table 3 – *Summary statistics*

3A – Entire dataset										
Variable	NITA	NIMTA	TLTA	TLMTA	CMTA	EXRET	SIGMA	RSIZE	MB	PRICE
Obs.	353.7	353.7	356.8	356.8	338.6	310.8	316.1	326.5	367.2	331.4
Mean	-0.06	-0.04	0.64	0.60	0.07	-0.05	0.59	-2.45	2.25	1.93
Std. Dev.	0.08	0.09	0.28	0.32	0.11	0.19	0.46	1.39	4.03	1.27
Min	-0.14	-0.10	0.09	0.02	0.00	-0.70	0.10	-7.01	-9.17	-2.14
Max	0.09	0.13	1.22	0.88	0.80	0.64	2.80	1.32	17.16	2.70
3B – Pre-bankruptcy group										
Variable	NITA	NIMTA	TLTA	TLMTA	CMTA	EXRET	SIGMA	RSIZE	MB	PRICE
Obs.	348.7	348.7	351.7	351.7	333.7	306.4	311.6	321.3	362.0	326.7
Mean	-0.06	-0.04	0.64	0.60	0.07	-0.05	0.59	-2.38	2.27	1.94
Std. Dev.	0.07	0.08	0.28	0.32	0.11	0.19	0.46	1.25	4.01	1.27
3C – Post-bankruptcy group										
Variable	NITA	NIMTA	TLTA	TLMTA	CMTA	EXRET	SIGMA	RSIZE	MB	PRICE
Obs.	5.0	5.0	5.1	5.1	4.9	4.4	4.5	5.3	5.3	4.7
Mean	-0.08	-0.07	0.73	0.65	0.05	-0.08	0.60	-6.92	1.33	1.58
Std. Dev.	0.12	0.17	0.25	0.21	0.18	0.19	0.52	1.88	5.18	1.04

Note: number of observations is in thousands.

3.2.1 Entire Dataset

Our dataset contains approximately 345,000 firm-quarters for each independent variable; this implies that on average the company in our sample stays active for 32.9 quarters or 8.2 years. We acknowledge that this is probably an under-statement caused by the missing data issue, although the latter could be driven by several natural factors, such as mergers & acquisitions

[11] We are not providing a separate summary for the pre-bankruptcy group given that variable distributions are approximately similar to the entire sample; of note, pre-bankruptcy group constitutes 98.5% of the firm-quarters in the entire dataset.

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or voluntary de-listings. At the same time we recognize that some firm-quarters are missing purely for data quality reasons, which was discussed in details in the previous section.

We then analyze the distribution within our dataset with respect to firm`s size, which we roughly approximate[12] with the book value of total assets. Interestingly, we find that less than 40% of our firm-quarters exceed $100 million in value, while only about 7% exceed the $500 million watermark. Given that we weight each firm-quarter equally, this finding suggests that the distribution of our data is primarily dominated by smaller firms. This feature helps to explain some of the distribution characteristics for several variables presented in the table above. Specifically, mean values of NITA and NIMTA are both slightly negative while their distributions are significantly skewed to the left. These could result from the tendency of smaller firms to exhibit lower return on capital due to a lack of sufficient operating leverage and market power, among other factors (Pervan, 2012).

We also find that mean firm`s stock price performance relative to the broad index, as evidenced by EXRET, is slightly negative, which suggests that on average companies in our sample have under-performed the S&P 500 index. Although this finding is somewhat counter-intuitive, we argue that it is primarily related to a combination of two factors: the time frame selected for our sample on the one hand, and cyclical nature of initial public offerings on the other[13].

To illustrate the former, our sample captures three major "hot" IPO periods[14], with the largest spike taking place in 1999, when total dollar volume raised exceeded $108.1Bn. To put this into prospective, it is approximately 300% of the 1994-2018 annual average. Further, should we combine total dollar amount raised during the top-5 "hot" years, it amounts to over $350Bn,

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[12] More reliable proxies for firm`s size, such as number of employees or inflation-adjusted financial metrics are not readily available at CapitalIQ / Thomson Reuters Eikon or have significant gaps in data.
[13] Please recall that our sample includes only publicly-traded firms.
[14] 1998-1999, 2006-2007 and 2013-2014.

which is 40.4% of the total dollar value raised over the 25-year time frame (Marderosian 2017). At the same time we note that IPO activity generally peaks at or near the top of an economic cycle as firms aim to maximize dollar amount raised per share; during these "hot" periods investors` excessive optimism can drive demand for IPO subscriptions meaningfully above the supply, which in turn pushes stock price above its fundamental value. However, as markets cool down, prices tend to gradually decline, causing modest long-term underperformance post-IPO (Ritter, 1991).

The industry composition prospective in Table 4 shows that the sample is primarily dominated by four sectors: Consumer Discretionary, Health Care, Industrials and Information Technology. Combined, they represent approximately two thirds of both the number of firms in the dataset and the number of bankruptcy events. While this concentration primarily reflects high level of market fragmentation in these industries, discussing this matter in further details lies beyond the scope of our research.

Table 4 – *Chapter 11s and 22s breakdown by industry*

Industry	**Number of Firms**	**% of Total**	**Chapter 11s**	**% of Ch. 11 to Number of Firms**	**Chapter 22s**
Communication Services	948	9.10%	93	9.80%	-
Consumer Discretionary	1,452	13.90%	184	12.70%	9
Consumer Staples	564	5.40%	45	8.00%	-
Energy	960	9.20%	99	10.30%	5
Health Care	1,887	18.10%	137	7.30%	-
Industrials	1,554	14.90%	125	8.00%	2
Information Technology	1,966	18.90%	144	7.30%	4
Materials	741	7.10%	48	6.50%	3
Real Estate	165	1.60%	4	2.40%	-
Utilities	181	1.70%	11	6.10%	-
Total	**10,418**	**100.00%**	**890**		**23**

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3.2.2 Post-Bankruptcy Group

Comparing Tables 3.B and 3.C illustrates that the number of firm-quarters in the post-bankruptcy group is considerably lower; this is primarily driven by the fact that only about 63% of companies file for reorganization under Chapter 11, while this value narrows down to only 37% for firms that successfully emerge from bankruptcy; about 27% in our sample files straight into liquidation under Chapter 7. However, there are cases when a court or a company itself decides to convert from Chapter 11 into Chapter 7, or vice versa. Interestingly, approximately 1% of firms in our sample initially filed for Chapter 7 but were re-organized and continued to operate as a going concern. Table 5 summarizes the distribution by the type of bankruptcy filing.

Table 5 – *Bankruptcy by filing type*

Filing Type	**Number of Chapter 11s**	**% of Total**	**Number of Chapter 22s**	**% of Total**
Chapter 7	152	17%	7	30%
Chapter 11, Emerge	328	37%	6	17%
Chapter 11, Not Emerge	234	26%	8	43%
Chapter 11 into 7	158	18%	1	4%
Chapter 7 into 11	7	1%	-	0%
Other	11	1%	1	4%
Total	**890**	**100%**	**23**	**100%**

Table 3 also suggests several intuitive conclusions: compared to the pre-bankruptcy group, companies that faced and survived the first bankruptcy, on average, tend to have modestly lower profitability, higher leverage, weaker liquidity, and their stock returns generally under-perform the broad market by a larger amount. These findings are general consistent with Altman (2009).

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CHAPTER 4. METHODOLOGY

In order to estimate the probability of the first Chapter 11 filing, we employ the time-discrete hazard model that was first adapted for bankruptcy prediction by Shumway (2001) and later used by Campbell et al (2008). This approach has several benefits compared to the multiple-discriminant analysis used by Altman (1968), as well as the single-period logit model that was first developed by Ohlson (1980), which are both examples of a static model. To illustrate, Shumway (2001) argues that static bankruptcy prediction models might produce biased and inconsistent results as they take into account only a snapshot based on a single period prior to the bankruptcy filing and ignore the period at risk factor; in contrast, hazard models capture the dynamics of independent variables, hence avoid the selection bias described above. Further, Shumway and Chawa and Jarrow (2004) find that hazard models produce more efficient results as they exploit more data that is available.

4.1 Model Construction

As time-discrete hazard models have the same likelihood function as logit models, their asymptotic variance-covariance matrixes are also identical (Shumway 2001). This finding suggests that we can use a more convenient multi-period logit model to estimate the probability of both the first and subsequent defaults.

However, before doing so we need to account for several factors. First, standard logit model will produce incorrect t-statistics as it assumes that all firm-quarters are independent. Clearly, this assumption doesn’t hold for the within-firm time-series observations in our dataset. We correct for this lack of independence via making an appropriate adjustment to the sample size: we cluster all observations into groups by the unique firm identifier so that the number of clusters is equal to the number of firms (Hilbe 2009).

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Second, we need to make sure that the structure of our data and the model used are fully compatible. By their nature, hazard models ignore observations that take place after the pre-specified event occurs; to illustrate, both Shumway (2001) and Campbell et al (2008) estimate the probability of the first default and completely disregard any repeated filings or the firm`s performance should it survive the first bankruptcy. Because we are interested in predicting both Chapter 11 and Chapter 22, we run Model 1 and Model 2 based on the pre- and post-bankruptcy groups, respectively, hence adhere with the compatibility requirement.

Following Shumway (2001) and Campbell et al (2008), we then assume that the marginal probability of a bankruptcy event happening during the next quarter has the following form:

$$P_{t-1}(Y_{it} = 1) = \frac{1}{1 + e(-\beta_1 k_{t-1} - \beta_2 x_{i,t-1})}$$

where Y_{it} represents the binary indicator of the event of default for a given firm *I* in a given quarter *T*, *X* is a set of firm-specific characteristics represented by various financial and equity market factors, and K is a so-called "baseline of a hazard function", which defines the hazard rate of a firm in absence of other covariates (Shumway 2001).

Regarding the former, Shumway (2001) argued that the probability of default in a given year is a function of the firm`s age. In order to test this hypothesis, he transformed the proportional hazard model into an accelerated failure-time model by adding a natural logarithm of age[15] in his model as a baseline of a hazard function; however, he found this factor to be statistically insignificant. Based on this conclusion, Campbell et al (2008) simply omitted the firm`s age from their model while keeping only financial and equity market regressors. In doing so, they

15 Approximated with a number of years the company has been publicly listed on the NYSE or AMEX.

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implicitly switched to estimating an exponential hazard model which assumes that the probability of the firm`s default is determined solely by firm-specific factors.

However, using the exponential hazard model might not be an optimal approach for predicting corporate bankruptcy over a long term as it ignores other potentially important predictors such as the firm`s industry classification or macroeconomic environment (Duffie et al 2007, Bottazzi et al 2011). In order to test this hypothesis we experiment with a broad range of candidates for a baseline of a hazard function; we discuss our findings in the "Results and Discussion" section.

Further, based on Table 4 we argue that the probability of default is not uniform across all industry groups. This hypothesis has strong support across both academic researchers (Chawa and Jarrow 2004, Couderc and Renault 2008) and industry practitioners (Vazza and Kraemer 2017). Naturally, we would expect that firms in industries like consumer discretionary and technology are prone to higher probability of default compared to utility or real estate companies due to the nature of their business alone. In order to test for the industry effect, we included a set of dummies for each industry group as an additional baseline function.

4.2 Applying Hazard Models to the Post-Bankruptcy Sample

We then apply various specifications of hazard bankruptcy prediction models to the post-bankruptcy sample. We hypothesize that the fundamental factors that determine the company`s operating performance trajectory before and after the successful[16] re-organization are similar, hence both the traditional and the hybrid specifications can also prove to be useful frameworks for predicting Chapter 22s (Hypothesis 1).

Although existing body of economic research on this topic is limited, combining piecewise findings from various sources provides some theoretical support to this hypothesis. To

[16] By "successful" in this context we mean that the firm emerged from the bankruptcy.

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illustrate, Altman et al (2009) argues that higher leverage and lower profitability are associated with higher probability of both first and repeated corporate bankruptcy; interestingly, he also finds that firm`s liquidity[17] is an insignificant predictor of Chapter 22. Further, several scholars suggest that on average, market gauges correctly the firm`s future prospects during the reorganization process and after emergence (Alderson & Betker 1999, Gilson et al 2000), although the dispersion of valuation errors is wide (Gilson et al 2000); provided that the valuation is, on average, unbiased, we can expect some or all of the market-based factors employed by Shumway and Campbell to retain their fundamental ties to the probability of default of a reorganized firm.

4.3 Model Specifications

In order to estimate the probability of the first default, or Chapter 11, we begin with constructing Model 1.1 based on two traditional financial ratios, NITA and TLTA, and three equity market-based variables, namely EXRET, RSIZE, and SIGMA (Shumway 2001). See Table 6A in the "Results and Discussion" section.

We then turn to estimating Model 1.2, which extends the previous specification via incorporating three new variables and adjusting the financial ratios for the market value of assets (Campbell et al 2008): in total, it contains three hybrid[18] financial ratios, NIMTA, TLMTA and CMTA, and five market-based factors, EXRET, RSIZE, SIGMA, MB and PRICE. See Table 6A for further details.

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[17] Although he uses a different proxies for leverage (Book Value of Equity / Total Assets), profitability (EBIT / Total Assets) and liquidity ([Current Assets – Current Liabilities] / Total Assets).
[18] For convenience, hereafter we sometimes refer to Shumway`s specification as the "traditional model" and to Campbell`s specification as the "hybrid model".

As a next step, we test for a potential performance improvement within both models from adding a macroeconomic factor as the baseline of a hazard function; we mark the macro-adjusted specification with a postscript “A” (eg. Model 1.1A) going forward.

Finally, following Chawa and Jarrow (2004) we test for industry effects across all specifications by adding nine industry dummies. We do not include the first group, “Industrials”, as we use this sector as a base for comparison. We report the industry-adjusted specifications with a subscript “B” (eg. Model 1.1B).

After testing the performance of the Shumway and Campbell`s specifications on the pre-bankruptcy group, we proceed with evaluating how these models fit the post-bankruptcy data. Should the results support Hypothesis 1, we will first test both specifications for the presence of redundant covariates, and then evaluate if macroeconomic and industry factors add value to the models` performance. We report those as Models 2.1 – 2.2B in Table 6B.

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CHAPTER 5. RESULTS AND DISCUSSION

5.1 Predicting Chapter 11

Table 6A - *Predicting initial bankruptcy*

	Chapter 11					
Specification	**1.1**	**1.1A**	**1.1B**	**1.2**	**1.2A**	**1.2B**
NITA	-0.85 (0.22)**	-0.82 (0.22)**	-0.90 (0.21)**	-	-	-
NIMTA	-	-	-	-0.97 (0.21)**	-0.97 (0.21)**	-1.04 (0.21)**
TLTA	2.48 (0.21)**	2.47 (0.21)**	2.49 (0.23)**	-	-	-
TLMTA	-	-	-	4.36 (0.51)**	4.26 (0.52)**	4.08 (0.52)**
CMTA	-	-	-	-1.80 (0.90)*	-1.93 (0.91)*	-1.82 (0.92)*
EXRET	-2.31 (0.46)**	-2.21 (0.46)**	-2.19 (0.46)**	-1.44 (0.43)**	-1.41 (0.43)**	-1.44 (0.44)**
RSIZE	-0.26 (0.08)**	-0.30 (0.08)**	-0.32 (0.08)**	0.07 (0.09)	0.05 (0.09)	0.07 (0.10)
SIGMA	0.61 (0.17)**	0.45 (0.18)**	0.43 (0.18)*	0.80 (0.20)**	0.72 (0.20)**	0.78 (0.20)**
PRICE	-	-	-	-0.32 (0.05)**	-0.31 (0.05)**	-0.24 (0.05)**
MB	-	-	-	-0.02 (0.04)	-0.02 (0.04)	-0.02 (0.04)
MSPRD	-	0.37 (0.08)**	0.38 (0.08)**	-	0.20 (0.09)*	0.20 (0.08)*
CONSDISC (IND3)	-	-	1.28 (0.18)**	-	-	1.10 (0.19)**
Intercept	-10.17 (0.19)**	-11.06 (0.27)**	-11.44 (0.29)**	-10.08 (0.41)**	-10.51 (0.41)**	-10.70 (0.41)**
Observations	293,271	293,271	293,271	293,271	293,271	293,271
Pseudo R2	0.1391	0.1477	0.1651	0.2160	0.2219	0.2320

*Note: Table 6A reports the logit regression results for each model specification (rows) based on a set of predictors defined in the previous sections (columns). "Chapter 11" group denotes models that are based on the pre-bankruptcy sample. CONSDISC represents the industry dummy for the Consumer Discretionary industry group. CONS is the intercept coefficient. We use cluster robust standard errors for each specification; * denotes significant at 5%, ** denotes significant at 1%. We report McFadden`s Pseudo R-squared for each specification, in line with Campbell et al (2008).*

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5.1.1 Model 1.1

The first column of Table 6A represents the results of the Shumway specification. All of the five variables of interest enter with an expected sign and are statistically significant at the 1% level: the model suggests that higher leverage (TLTA) and stock price volatility (SIGMA) are generally associated with higher probability of default. At the same time, higher excess return over the S&P 500 index (EXRET), higher profitability (NITA) and larger relative size compared to the value of the S&P 500 index (RSIZE) tend to push the dependent variable in the opposite direction.

5.1.2 Model 1.2

We then move to the Campbell hybrid specification (see column 4 of Table 6A) by first substituting NITA and TLTA with their market-adjusted equivalents, and then adding three new variables (CMTA, PRICE and MB) to Model 1.1. Except for RSIZE, coefficients on the initial set of market-based regressors from the Shumway specification (EXRET and SIGMA), as well as the market-adjusted financial ratios (TLMTA and NIMTA) are all highly statistically significant and have the expected signs that are in line with the previous specification.

However, RSIZE turns out to be statistically insignificant in the hybrid model. While we view this factor as an important predictor of corporate default in line with both Shumway and Campbell, we argue that in this specification it is meaningfully affected by a considerable correlation with stock price volatility SIGMA and stock price PRICE, which appear in the model with opposite signs and have very strong predictive power. As reported in Table 7A, fitted coefficients of RSIZE, SIGMA and PRICE are highly correlated. However, the Wald test suggests that these variables are jointly significant at the 1% level. Intuitively, high correlation among these factors might reflect the following tendency: an increase in stock price volatility, or risk, generally drives the cost of equity up; this directly flows into higher discount factors

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used by investors to valuate the stock`s fair value, and hence leads to a decline in stock price both in absolute terms and relative to a diversified index (S&P 500 in our case).

Table 7A - *Correlation Matrix of Independent Variables, Pre-Bankruptcy Group*

	NIMTA	*TLMTA*	*CMTA*	*EXRET*	*RSIZE*	*SIGMA*	*PRICE*	*MB*	*MSPRD*
NIMTA	1.00								
TLMTA	-0.08	1.00							
CMTA	-0.07	-0.13	1.00						
EXRET	0.14	-0.15	-0.05	1.00					
RSIZE	0.29	-0.15	-0.12	0.15	1.00				
SIGMA	-0.26	0.08	-0.03	-0.05	-0.69	1.00			
PRICE	0.19	-0.12	-0.01	0.10	0.50	-0.37	1.00		
MB	0.06	-0.37	-0.09	0.10	0.11	0.00	0.07	1.00	
MSPRD	-0.07	0.07	0.08	-0.03	-0.06	0.18	-0.08	-0.04	1.00

Further, column 4 of Table 6A suggests that two out of three regressors introduced by Campbell are statistically significant based on our sample, namely the measure of the firm`s immediate liquidity position CMTA and share price PRICE; in line with the original results, both have negative signs, suggesting that firms with higher proportion of cash balances to the market value of assets and higher share price tend to have lower probability of facing bankruptcy. The remaining of the three, MB, has the correct sign but is not statistically different from zero. We note, however, that this factor was included in the original model not as a variable of interest, but rather as a correction factor for both NIMTA and TLMTA: it was designed to capture an increased probability of bankruptcy for drastically overvalued firms (Campbell et al, 2008).

One final conclusion from comparing columns 1 and 4 of Table 6A is that the Campbell specification delivers a material improvement in explanatory power compared to the Shumway Model 1.1, which is primarily driven by two adjustments: switching to the market-adjusted leverage metric TLMTA and adding PRICE. Specifically, as we move from Model 1.1 to 1.2, these two adjustments yield an improvement in the R-squared of 198 and 252 basis points, respectively.

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5.1.3 Model 1.1A and 1.2A

We then extend both the traditional and the hybrid specifications by including the macroeconomic factor as a baseline function. Among the three potential candidates for this role, we chose the Moody`s credit spread (“MSPRD”) as it over-performs the percentage change in real GDP growth and the percentage points change in the FED rate in terms of economical and statistical significance within both specifications[19].

As evidenced in the second and fifth columns of Table 6A, MSPRD enters both the Shumway and Campbell`s specifications with a positive sign and is statistically significant[20]. The direction of this relationship suggests that the wider the credit spread is, the higher the probability of corporate default. This finding is in line with the fact that the size of the credit spread is inversely related to the level of real economic activity: it hits its lowest at or somewhat prior to the peak of an economic cycle, and then tends to widen as economy slows down or moves into a recession (Gilchrist and Zakrajsek 2010). Consequently, as the credit spread widens, paying floating interest rates, raising new debt and refinancing existing obligations become more and more challenging, which in turn can push a larger number of companies into default during economic downturns.

Finally, we acknowledge that introducing the macroeconomic variable as a base of the hazard function brings in a modest improvement in explanatory power within both specifications; it also significantly[21] affects the intercept and several slope coefficients, thus can improve the models` forecasting ability.

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[19] Note that these three macroeconomic factors have over 80% correlation among each other, hence we only include the most efficient one.
[20] Although at different levels: at 1% in Model 1.1a and at 5% in Model 1.2a.
[21] The null hypothesis is that coefficients are identical between the baseline and the macro-adjusted model. In comparing Model 1.1 and Model 1.1a it is rejected at 1% for CONS, EXRET, RSIZE and SIGMA. In the Campbell specification it is rejected at 5% for CONS, TLMTA, SIGMA and PRICE. We fail to reject the null for other variables.

5.1.4 Model 1.1B and 1.2B

Columns 3 and 6 of Table 6A represent the final adjustment to both specifications: in order to test for a potential industry effect, we add a set of dummies to Model 1.1A and 1.2A for each industry group, taking "Industrials" as a base for comparison to avoid perfect multicollinearity. We find that while for other sectors of economy the effect is statistically insignificant, on average, firms from the "Consumer Discretionary" group exhibit a considerably larger probability of facing Chapter 11 compared to the base group[22]. Note that taking the industry effect out of the residual term provides a considerable improvement in explanatory power across both models without any material effect on other coefficients or the intercept.

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[22] The coefficient is significant at the 5% level in both models.

5.2 Predicting Chapter 22

Table 6B – *Predicting repeated bankruptcy*

	Chapter 22					
Specification	**2.1**	**2.1A**	**2.1B**	**2.2**	**2.2A**	**2.2B**
NITA	-1.65 (0.61)**	-1.63 (0.58)**	-2.06 (0.77)**	-	-	-
NIMTA	-	-	-	-1.65 (0.67)*	-1.97 (0.37)**	-2.19 (0.49)**
TLTA	4.28 (1.84)*	4.32 (1.87)*	4.19 (1.86)*	-	-	-
TLMTA	-	-	-	3.92 (1.97)*	5.05 (2.28)*	3.96 (2.01)*
CMTA	-	-	-	-8.62 (7.72)	-	-
EXRET	-2.71 (1.95)	-2.75 (2.01)	-2.57 (1.86)	-2.56 (2.08)	-	-
RSIZE	-0.45 (0.22)*	-0.44 (0.32)	-0.57 (0.28)	-0.35 (0.17)*	-0.53 (0.15)**	-0.65 (0.16)**
SIGMA	-2.04 (0.75)*	-1.98 (0.78)*	-2.26 (0.81)**	-2.04 (0.90)*	-1.52 (0.71)*	-1.78 (0.81)*
PRICE	-	-	-	-0.15 (0.16)	-	-
MB	-	-	-	-0.19 (0.04)**	-0.18 (0.05)**	-0.20 (0.06)**
MSPRD	-	-0.15 (0.55)	-0.06 (0.56)	-	-	-
CONSDISC (IND3)	-	-	2.12 (0.78)**	-	-	1.97 (0.82)*
Intercept	-8.77 (1.36)**	-8.45 (1.70)**	-9.40 (2.06)**	-7.19 (1.82)**	-8.72 (1.60)**	-9.01 (1.58)**
Observations	4,118	4,118	4,118	4,118	4,118	4,118
Pseudo R2	0.1362	0.1371	0.2064	0.1622	0.1351	0.1666

*Note: Table 6A reports the logit regression results for each model specification (rows) based on a set of predictors defined in the previous sections (columns). "Chapter 11" group denotes models that are based on the pre-bankruptcy sample. CONSDISC represents the industry dummy for the Consumer Discretionary industry group. CONS is the intercept coefficient. We use cluster robust standard errors for each specification; * denotes significant at 5%, ** denotes significant at 1%. We report McFadden`s Pseudo R-squared for each specification, in line with Campbell et al (2008).*

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5.2.1 Model 2.1

The next step is to test the suitability of Models 1 and 2 for predicting repeated bankruptcy, or Chapter 22. We begin by testing the performance of the Shumway specification on the post-bankruptcy sample (column 1 of Table 6B), taking the Model 1.1 results as a benchmark. We find that four out of five variables enter the model significantly (NITA, TLTA, RSIZE and SIGMA); three out of those four enter with the expected signs (NITA, TLTA and RSIZE).

Interestingly, SIGMA flipped in sign to negative as we move to Model 2.1, suggesting that higher stock price volatility is associated with lower probability of Chapter 22. Although somewhat counterintuitive, we argue that this phenomenon could reflect the tendency of troubled firms` equity to trade at or slightly above the minimum allowable price[23] for a prolonged period of time after the first reorganization (Eberhart et al 1999); as a result, their stock has lower volatility due to limited downside. In other words, companies that manage to turn around their operating dynamic post-reorganization will experience a gradual rebound in their stock price after enterprise value exceeds the value of debtors` claims; as their stock price drifts further in the positive domain, the downside risk and price volatility also increases. In contrast, equity of those companies that emerged from the bankruptcy but failed to improve their operations, continues to trade near the lower bound with little to no signs of recovery.

The last variable of interest in the Shumway specification, excess return EXRET, retains its sign but turns out to be statistically insignificant in predicting the probability of Chapter 22. However, in contrast to Model 1.1, the standard error of this variable is likely to be significantly affected by multicollinearity in the post-bankruptcy sample (see Table 7B below); we discuss this issue in details in the end of this section.

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Table 7B - *Correlation Matrix of Independent Variables, Model 2.1*

	NITA	*TLTA*	*EXRET*	*RSIZE*	*SIGMA*	*MSPRD*
NITA	1.00					
TLTA	-0.20	1.00				
EXRET	0.02	-0.10	1.00			
RSIZE	0.45	-0.22	0.16	1.00		
SIGMA	-0.44	0.23	-0.06	-0.76	1.00	
MSPRD	-0.01	-0.02	-0.05	-0.01	0.13	1.00

[23] USD1.00 if stock continues to trade on organized exchanges like NYSE and USD0.01 in the over-the-counter markets.

The remaining characteristics reported in column 1 of both Table 6B and 6A reveal two additional findings that are worth mentioning. First, economic significance of both NITA and TLTA roughly doubles as we move from Model 1.1 to Model 2.1, implying that the firm`s fundamentals have a considerably larger predictive power in determining the probability of default for distressed or recently-reorganized firms compared to their healthy peers. Second, comparison of the pseudo R-squared values suggests that the Shumway model fits the post-bankruptcy data considerably well; this provides additional support to Hypothesis #1.

5.2.2 Model 2.2

We then proceed to estimating the Campbell specification based on the post-bankruptcy sample. As evidenced from column 4 of Table 6B, market-adjusted leverage TLMTA and profitability NIMTA enter significantly with expected signs. Similarly to Model 2.1, SIGMA also enters significantly with a negative sign.

Further, both RSIZE and MB are statistically significant and have expected signs in Model 2.2; the direction of their coefficients suggests that an increase in the firm`s share price relatively to both the value of the S&P500 index, and the book value of equity per share is associated with a lower probability of facing Chapter 22. In contrast, EXRET and PRICE are both insignificant although appear with expected signs in Model 2.2. Note that the aforementioned combination is the exact opposite of what we saw in Model 1.2, where the latter pair of covariates was statistically significant while the former was not.

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While this finding might hint at the presence of another major difference in the fundamental nature of the relationship between the covariates of interest on the one hand, and the probability of Chapter 11 and Chapter 22 on the other, we argue that this phenomenon is yet again driven by significant multicollinearity among several variables of interest (see Table 7C below).

Table 7C - *Correlation Matrix of Independent Variables, Model 2.2*

	NIMTA	*TLMTA*	*CMTA*	*EXRET*	*RSIZE*	*SIGMA*	*PRICE*	*MB*	*MSPRD*
NIMTA	1.00								
TLMTA	-0.05	1.00							
CMTA	-0.02	-0.15	1.00						
EXRET	0.09	-0.17	0.00	1.00					
RSIZE	0.29	-0.08	0.07	0.15	1.00				
SIGMA	-0.28	0.08	-0.11	-0.05	-0.75	1.00			
PRICE	0.20	-0.06	0.06	0.11	0.55	-0.41	1.00		
MB	0.07	-0.30	-0.03	0.09	0.17	-0.12	0.11	1.00	
MSPRD	-0.04	0.06	0.08	-0.05	0.00	0.12	-0.07	-0.05	1.00

5.2.3 Models 2.1A and 2.2A

Before adding macroeconomic and industry factors into Model 2.1 and 2.2, we test both for the presence of redundant variables in order to arrive at a parsimonious version of each specification first.

We start by excluding EXRET from Model 2.1, where it appears to be the only statistically insignificant variable (see Table 6B), and testing if the restricted model has better characteristics than the unrestricted one. Based on the Likelihood Ratio Test, or LRT, we reject the null hypothesis[24] at the 4.36% level, and hence keep the Shumway specification unchanged going forward arguing that EXRET remains an important predictor of Chapter 22 but only in combination with other regressors.

We then move to Model 2.2, which includes three insignificant covariates: CMTA, EXRET and PRICE. We exclude those in different combinations to arrive at six restricted models,

[24] H0 in the LRT is that the reduced model is nested in the full model.

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which we then test against the original specification. Table 8 suggests that we fail to reject the null hypothesis for all possible iterations at the 5% level; hence we drop out CMTA, EXRET and PRICE, and proceed with the restricted version of Model 2.2 going forward.

Table 8 - *Likelihood Ratio Test Matrix, Model 2.2*

Iteration	*1*	*2*	*3*	*4*	*5*	*6*
CMTA	Y	Y	Y	N	N	N
EXRET	N	Y	Y	N	Y	Y
PRICE	N	N	Y	Y	Y	N
P > chi2	12.51%	6.69%	6.21%	24.10%	8.14%	7.59%

**Y means the variable is excluded in this iteration*

Having the parsimonious models specified (column 5 of Table 6B), we then test if the macroeconomic factor MSRPD continues to play a viable role in predicting bankruptcy for the emerged firms. However, we find it to be statistically insignificant; further, LRT suggests that adding this parameter into the model brings no improvement in the model characteristics. Based on these, we conclude that unlike Chapter 11s, Chapter 22s are predominantly driven by firms` idiosyncratic factors and have considerably weaker ties to the economic cycle. Consequently, we drop MSPRD out before proceeding with the next step.

5.2.4 Models 2.1B and 2.2B

Finally, we test the importance of industry effects for predicting Chapter 22 by repeating the same exercise as in Models 1.1B and 1.2B (column 6 of Table 6B). Interestingly, we arrive at similar results, with "Consumer Discretionary" being the only industry group with a statistically significant coefficient, which suggests that this industry is prone to a larger probability of Chapter 22 compared to other sectors of economy. Note that the model fit also benefitted materially from adding the industry factor in both Model 2.1 and 2.2, which is likely related to the fact that approximately 40% of Chapter 22s in our sample occurred in the "Consumer Discretionary" sector.

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CHAPTER 6. SUMMARY

This thesis makes three main contributions to the existing body of research on financial distress. First, it examines how well do existing hazard models estimated by Shumway (2001) and Campbell et al (2008) fit the most recent quarter-century[25] of data for US-based, publicly traded companies. Second, it extends those state-of-the-art models by simultaneously fitting in both macroeconomic and industry factors, thereby modestly improving their explanatory power. Third, it evaluates how much of the variance in the probability of a repeated bankruptcy, or Chapter 22, can be explained with the factors that were originally employed by Shumway and Campbell for predicting the initial bankruptcy, or Chapter 11.

Our empirical analysis suggests the following conclusions. First, in predicting Chapter 11s over the 1994-2018 period, Shumway`s and Campbell`s specifications produce results that are consistent with the original findings, implying that the variables of interest retained their underlying relationships with the probability of the first default; also, both models fit our pre-bankruptcy sample considerably well, although Campbell`s specification has considerably stronger explanatory power in predicting Chapter 11. Second, both firm-specific and macroeconomic factors play an important role in predicting the probability of Chapter 11; in contrast, firms that remain distressed after being restructured tend to default irrespectively of the economic cycle. Also, base probability of default differs across industries, with firms in the Consumer Discretionary segment exhibiting a considerably larger probability of facing both Chapter 11 and Chapter 22. Third, parsimonious versions of both Shumway`s and Campbell`s specifications fit the post-bankruptcy data considerably well.

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[25] The 1994 – 2018 period.

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