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Are junk companies a good deal?
The value creation in turnarounds

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A special thanks to my family, for paving the way and inspiring me.

To Paolo, for being the North Star of my journey.

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Introduction

In 2020 there was a peak of distressed companies due to the economic crisis triggered by Covid-19. During the periods of downturn, distressed targets became particularly appealing, since on the market there are a lot of opportunities to purchase distressed securities at a very low percentage of their face value. However, the techniques to perform a correct valuation of high-yield companies are quite different from standard valuation methods, nevertheless, it is crucial to master them properly, since the inaccurate assessment of a troubled business can cause the investor to stumble into value traps.
In particular, equity prices of sub-investment grade companies are hugely influenced by the security's credit risk. Indeed, whereas the cost of capital of investment grade firms depends on the market risk, the cost of the capital of sub-investment grade firms depends mainly on the risk of default (Ermotti S. introduction to Oricchio (2012)). This dichotomy should be meticulously considered when assessing the equity risk premium in order to account for the default probability in the valuation process.

The world of distressed companies is quite complex since every firm has its peculiarities and it is challenging to find common grounds to categorize them into groups. For this reason, we started from the credit rating classes to identify sub-investment grade issuers which could fell into our definition of distress. The study considers a sample of 146 troubled companies, publicly traded in the European and American capital markets. The observed period spans from 2014 to 2019 and includes all firms with non-missing values for the measures chosen to estimate the value creation.

This dissertation fits into a gap in literature and research when it comes to the value creation perspectives of companies with a high risk of insolvency. In particular, we seek to assess whether investing in distressed companies creates value for shareholders. Thenceforth, the research investigates the drivers of the investors' wealth that can be spotted when highly distressed companies undertake a turnaround process, by performing a multivariate regression model. The focus is to identify which troubled companies to bet on, based on their intrinsic probability of surviving and becoming profitable again.

To answer the question "Are junk companies a good deal?" we will start from a descriptive statistic of the data sample, and we will then propose a model whose objective is to identify the value creation drivers. To do so we will follow a two-step process, firstly we will run a multivariate regression to test the identified indicators and to spot which are statistically significant, then we will proceed running an optimized regression of the variable that resulted significant in the first step.

This thesis is organized as follows. In the first section, we will present the reference context of the research, opening with the market outlook and describing the importance of the concept of default in the environment of distressed companies and how the default is connected to credit ratings and returns. The second chapter will propose an overview of the most relevant valuation method that can be implemented when evaluating sub-investment grade companies, along with some compelling reasons why standard valuation methods should be avoided in this context. Finally, in the third chapter, we will perform the empirical analysis of the shareholders' value creation. Further, we will present in detail the methodology employed and the variables considered in the research. We will then perform an analysis of the data sample and the dynamics of the population. At this point, we are going to implement our regression models, and we will conclude by explaining the results.

Chapter 1

1. RECENT DEVELOPMENTS IN THE REFERENCE CONTEXT

1.1 Market outlook

In 2020 the global macro-economic scenario has been overturned by the health emergency caused by the Covid-19 pandemic. At the beginning of last year, economic conditions changed dramatically, reflecting a worldwide downturn in economic activity unprecedented in modern history. According to IMF estimates, global GDP in 2020 fell by 3.3 per cent, representing the sharpest contraction since World War II. The recession negatively affected the international trade, which fell by 8.9 per cent, strongly driven down by the services contractions due to restrictions on the mobility of goods and people.
The economic effects of the Covid-19 crisis have varied across sectors and geographic areas, reflecting the severity of the health pandemic at the local level and the responses of governments' policies.

Monetary policies have prevented the pandemic crisis from turning into a financial crisis by ensuring liquidity in the markets and facilitating borrowing through various initiatives, including bond purchase plans. Tax policies have played a crucial role in supporting household and corporate incomes, especially in developed countries, and preventing a widening of the recession.
According to FMI estimations, the global economy is forecasted to grow 6.0 per cent in 2021 and 4.9 per cent in 2022.
It is difficult to assess the level of disruption truly faced by companies worldwide in 2020. Companies that sustained the liquidity shortage through capital raises now have higher debt levels and need to find new funding sources to bolster operations while demand levels are still uncertain.

The main difference between the Great Recession crisis and the Covid-19 crisis that we are experiencing today is that in 2008 the downturn started from the financial sector spreading like wildfire to every economic sector and triggering a contraction in demand widespread in every industry. Otherwise, the Covid-19 shock turned out more predictable and restricted to certain sectors, like leisure, transport, and aerospace, which were severely hit by the measures taken to limit the spread of the pandemic. Another point worth noting is that, as highlighted by Angeloni (2020) in the Great Financial Crisis the excessive risk-taking behavior of banks was the epicenter of the recession, now banks are themselves suffering from this unpredictable shock and are doing their part to mitigate its implications by keeping credit channels open.

Vaccine availability injected optimism and the expectation for a prompt economic recovery. Indeed, the access to vaccines has split the globe into two sides: advanced economies with broad access to vaccines, which can look forward to the recovery of business as usual already in 2021, and the countries still struggling with the Covid-19 pandemic (IMF, 2021).
A full economic recovery, however, is not guaranteed until the virus continues to circulate, and restrictive measures are around the corner.

1.2 Real GDP

In 2020, the GDP of advanced countries decreased by 4.7 per cent, with a contraction in investments and private consumption. The impact of the pandemic varied across countries and economic sectors. As shown by figure 1.1 the real GDP of the United States endured an average loss of 3.5 percentage points, which is considerably tinier than other major advanced countries. This was partly due to the fiscal measures, which were more robust than elsewhere, and to the lower magnitude of the restrictive measures adopted in the second half of the year.
According to ECB estimations, the eurozone's real GDP registered a 6.5 per cent contraction in 2020 and is expected to grow 6.0 per cent in 2021 and 4.9 per cent in 2022.

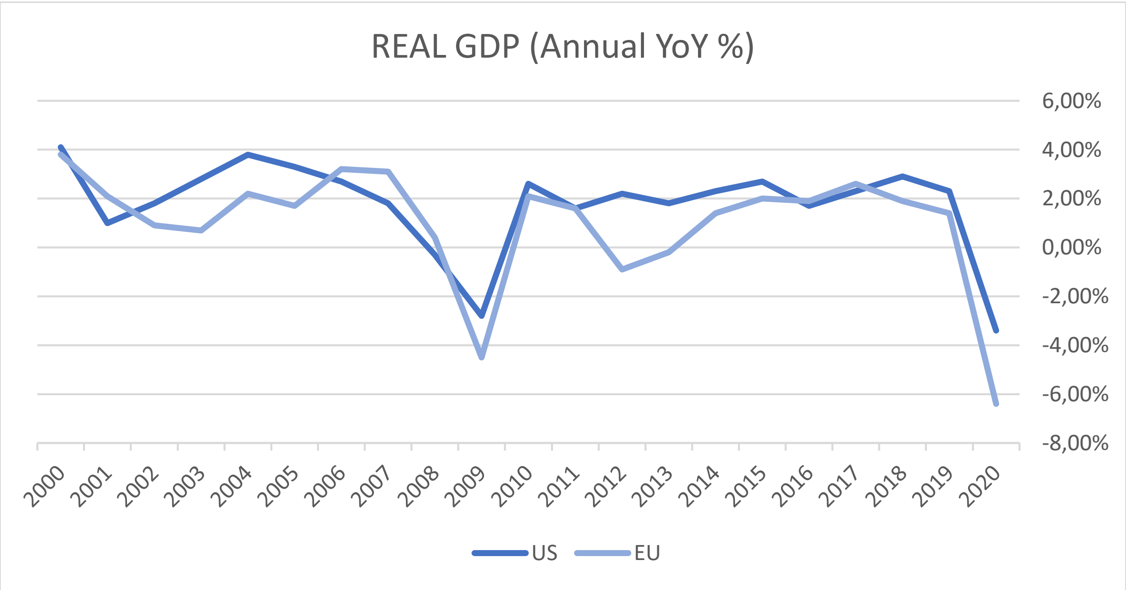

Figure 1.1 - Real GDP year-over-year variation (%)

Source: Bloomberg

Further, the contraction in the GDP triggered by the Covid-19 was driven by the shrinking of private consumption, due to restrictions and uncertainty, which reduced households' spending opportunities and fostered their propensity to save.
Muggenthaler (2021) notes that in countries such as Germany, Belgium, and the Netherlands, the real GDP's drop can be fully explained by private consumption, due to a very resilient external sector and a well-diversified exports composition. Moreover, also the others GDP constituents like total investment and net exports, even if they are of secondary importance considering their relative size, show a specific trend linked to a particular country and contribute to explaining the divergent GDP growth path in each country.

Based on data available up to date, ECB reports that in the first quarter of 2021 the real GDP in the eurozone was 4.9 per cent below its pre-recession level, after a decline of 6.5 per cent in 2020.

1.3 Business and credit cycle

The Covid-19 pandemic shock has touched many dimensions of the economy in a wave of disruption, and its implications are still difficult to predict.

In the pre-pandemic framework, around the end of 2019, the credit cycle appeared in a benign phase, even if with hindsight it is possible to say that there were already some red flags, not correlated with the pandemic, that later invested the markets. As shown by Altman (2020), observing the credit markets, there were already the first signs of a credit bubble, and the warning light was set on a "risk-on" indicator. This position is supported by the fact that in the US corporate and government bonds almost doubled from 2009, reaching a level of approximately $9 trillion at the end of 2019. Indeed, the highest growth was registered in the BBB-rating class, which accounted for about $3 trillion of bonds that were dangerously close to the investment-grade category. In conclusion, the ongoing issuance of high-risk debt up to the beginning of 2020, despite these red lights, denotes a debt bubble waiting to go off (Altman, 2020). We will never know if the debt bomb would have exploded without the hit of the pandemic, the only thing that can be noted is that the debt shape contributed to worsening the credit conditions after the Covid-19 shock in the leveraged loan market.

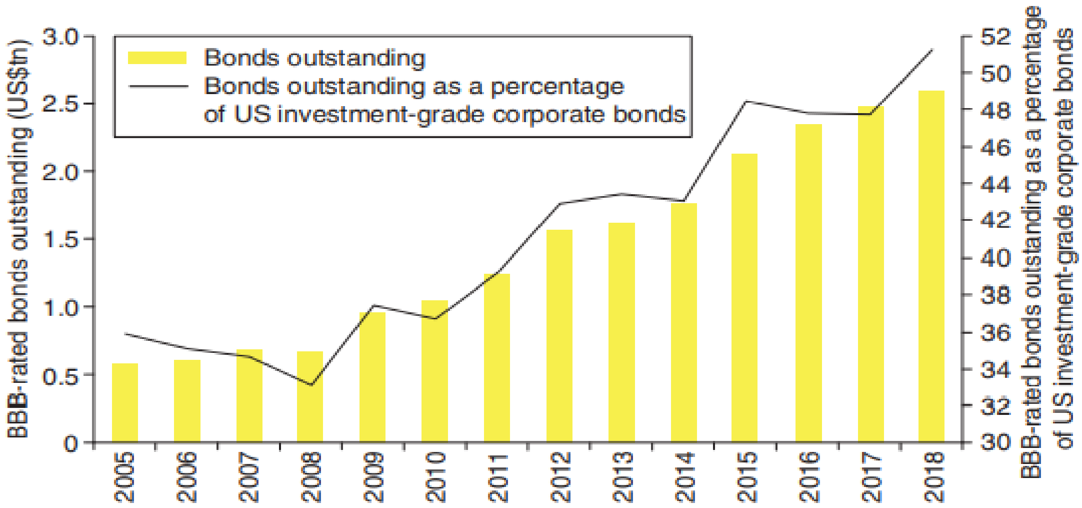

Figure 1.2 - US BBB-rated corporate bonds outstanding, 2005–18.

Source: Bloomberg Barclays US Corporate Investment Grade Index.

Now that there is light at the end of the pandemic tunnel, many are wondering about the recovery's shape and timeline. Looking back to the Great Recession of 2008-2009, the insight is that several advanced economies have not completely recovered yet, even after 10 years, and repercussions suffered by investors, companies, employees, and the public are far from being forgotten (Cerra et al., 2020). Further, it is worth noting that after the Great Recession the GDP never returned to grow according to the pre-crisis trend.

Moreover, history tells us that recoveries can be weak, thus not able to bring the GDP back to its pre-crisis trend. This is a demonstration that GDP shocks can switch from temporary to persistent in the following years, configuring themselves not only as movements along with the trend but also as events affecting and influencing the trend.

1.4 Bankruptcy activity in 2020

In 2020 Chapter 11 filings soared, increasing by about 29 per cent, going from 6.011 filings in 2019 to 7.743 in 2020, according to the Bloomberg BANBT11 index, which accounts for all new US bankruptcy filings concerning the business category.[1] However, the rise in bankruptcy activity can be considered modest if we compare it to the disruption that companies were forced to tackle in 2020,

[1] The BANBT11 index includes filings of Chapters 7,11,12, and 13. Bloomberg takes the data from the Administrative Office of the US Courts statistical division.

thanks to government aids and availability of liquidity, which led to fewer corporate restructurings than expected by economists.

Further, it's been proven that the Covid-19 crisis has been the catalyst to further the restructuring of companies that had already shown signs of trouble before the pandemic. According to a PWC estimation, approximately nine of the ten largest companies that decided to file for Chapter 11 were already on distressed watchlists at the beginning of 2020, as a demonstration that the pandemic impact was not the primary cause of distress for these businesses.
Moreover, the industries most hit by the restructurings wave are retail, energy, travel, and hospitality, which suffered a huge decrease in demand due to restrictive measures.

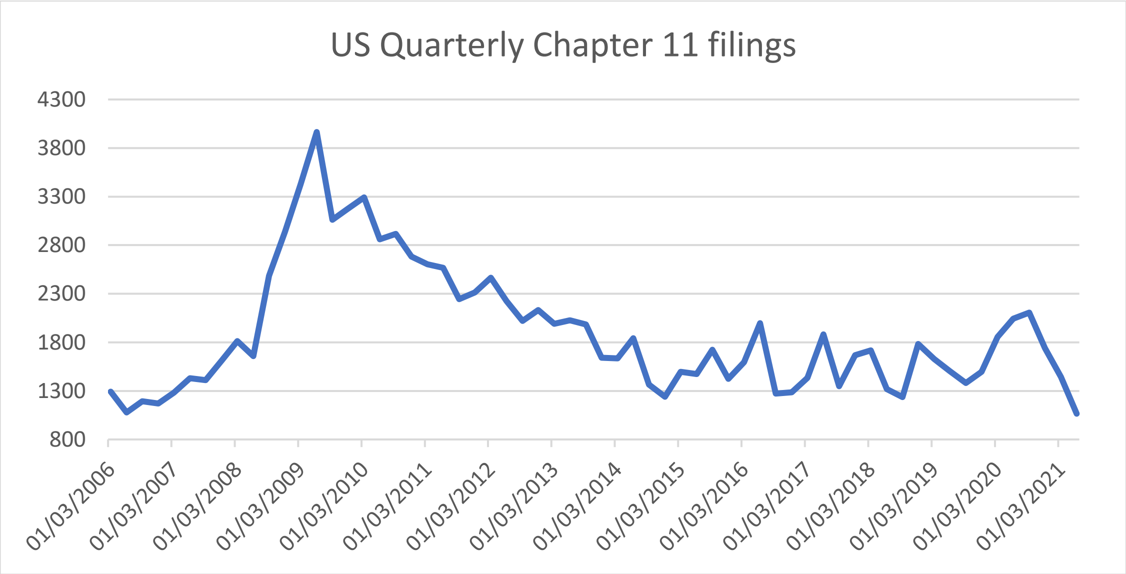

Figure 1.3 - US new bankruptcy cases chapter 11 business filings

Source: Bloomberg

As shown in figure 1.3, the number of bankruptcies reached its highest since 2012, but not quite as the peak hit after the Great Recession, when there were 8.896 filings registered in 2008 and 13.632 in 2009, according to Bloomberg.

Further, as clarified by Dun *et al.* (2019), bankruptcies can be considered a lagging indicator, since creditors and debtors tend to postpone the filing for Chapter 11 protection because of their reluctance to realize losses when assets fair value is unsure due to the downturn period. Moreover, especially companies that have assets with a meager recovery value are more unlikely to file for bankruptcy because the costs to bear are higher than the possible gains. Even banks happen to delay the

foreclosing on debts when banking profits are exiguous, which is parallel to the recession that originated the failures in the first place, to limit bad loan provisions when their profit and loss accounts are already suffering.
If we look back to the path taken by the Great Recession, we can notice that lenders with distressed positions were most likely to foreclose sooner, whereas on the contrary creditors suffering from a lower level of distress were likely to delay.

For the aforementioned reasons, when the markets will stabilize and the post-pandemic picture will be clearly defined, creditors will be able to better estimate the value of the collaterals and will take actions, causing an inevitable rise in the restructuring activity and, therefore, in the number of filings for Chapter 11 protection.

1.5 Governments and banks support

The pandemic and the necessary restrictive measures have led to social and economic shock without precedent. Government and central banks support have been crucial to hold back and limit insolvency and restructuring activity. In Italy, companies' cost burden has been released with the use of public money, through funds for pending layoffs, non-repayable transfers, deferral of tax and social security contributions, and a moratorium on loans. As reported in the *CXXVII Relazione Annuale* (2021), in 2020 the US Government issued multiple tax plans, worth $3.5 trillion, split among direct fiscal transfers, labor market subsidies, and credits to support the productive sector, which all together contributed to increasing the budget deficit to 15.8 per cent of the GDP. In the eurozone, the liquidity injected by the ECB in the banking system increased by €2.200 billion as a result of actions taken by the central bank to support financing conditions in the economy and to safeguard price stability over the medium term.

Thus, the government support measures prevented the exit from the market of firms whose difficulties were temporary. However, governments cannot afford to foot the bills forever and unfortunately, the ramifications of the downturn are not visible yet. As countries will start to gradually withdraw support, the restructuring activity that has been fictitiously avoided is set to pick up.

In this framework, banks benefited from an increase in the credit demand, given that companies with revenue shortfalls draw on their credit lines, oftentimes encouraged by public guarantees on credits. However, this fresh air for banks' revenues may be dampened by the deterioration of credit quality in the wake of the recession. Despite the expectations, supervisory statistical reports haven't shown signs of credit quality deterioration yet. Further, Angeloni (2020) reports data regarding the (gross) NPL ratio in the eurozone, and surprisingly, starting from 3 per cent at the end of 2019, it decreased to 2.8 per cent in September 2020. Nevertheless, the ECB provides evidence that shows how the benign phase experienced until this point will terminate soon and NPLs will likely rise in the post-Covid era. In terms of numbers, in September 2020 NPLs in European banks' books were worth over €550 billion (about 2.8 per cent of the total amount of loans). The ECB estimated that in the worst (but plausible) case scenario, NPLs could rise to an amount of €1.4 trillion by the end of 2022. Moreover, according to Angeloni (2020), the measures taken by eurozone supervisors to solve the problem of NPL raised in the wake of the Great Recession, such as the calendar provisioning and the accounting treatment of NPLs, may not be effective in this circumstance, due to an excessive rigidity (lack to adapt to the peculiarity of each bank) and high sensitivity to the uncertainty of the present situation.

Indeed, these implications will become visible with a significant time lag, after the withdrawn of governments' support. On the other end, firms that bolstered liquidity through capital increases will face higher financial expenses and will come to terms with more levered balance sheets tiding their hands in a period of economic uncertainty and will likely be forced to restructure.

1.6 Default probability

1.6.1 Default definition

Financial default occurs when a borrower fails to repay a debt, including interest or principal and assumes the status of non-performing. Moody's default definition, which applies only to debt or debt-like obligations, states that an issue or an issuer is in default if one of the following events occurs:

- A missed or delayed repayment of a contractually obligated interest or principal, whereby the payment default is not disbursed within the grace period.
- A bankruptcy filing, either a Chapter 7 (liquidation) or Chapter 11 (reorganization), by the debt issuer or obligor that will presumably trigger a miss or delay in future contractually binding payments. In this instance, all liabilities of the bankrupt entity are considered in default.
- A distressed exchange (DE) whereby a debt issuer presents to creditors a tender-offer, which can involve a new or restructured debt, or a new package of securities, cash, or assets, that amount to

a diminished value relative to the debt obligation's original promise and the swap has the effect of allowing the issuer to avoid a likely eventual default.

- A change in the payment terms of a credit agreement or indenture determined by the sovereign results in a lower financial obligation, such as a constrained currency re-denomination or a variation in some other terms of the original promise, such as indexation or maturity.

Recently the EBA introduced new guidelines regarding the definition of default with the Article 178 of Regulation (EU) N° 575/2013[2], which states that, concerning the classification of clients by banks and financial intermediaries, a borrower is to be considered defaulted if at least one of these two conditions is met: a) the institution considers that the obligor is unlikely to pay its credit obligations in full without realization of collateral; b) the obligor is past due more than 90 days on any material credit obligation to the institution.[3]

1.6.2 Global default and credit rating

Credit rating is designed to assess the quality of bond issued, measured in terms of the issuer's estimated solvency and its likelihood of default. There are three major credit rating agencies: Moody's, S&P Global, and Fitch ratings, which control approximately 95% of the rating industry. Credit ratings are fundamental variables to which investors look at to evaluate the bonds' credit risk, especially in the non-investment grade sector.
Further, credit ratings can be considered as a proxy for companies' default probability, thus facilitating investors to assess the value of financial instruments and determine their appropriate required yield consistent with their default risk (Wojewodzki et al., 2018).
Figure 1.4 shows the rating hierarchy utilized by the three major rating agencies to translate credit and default risk into standardized ratings. The rating scales are generally split into two groups, between the safer investment-grade securities (from Aaa to Baa3/AAA to BBB–) and the riskier high-yield bonds (below Baa3/ BBB–).

[2] Article 178 of Regulation (EU) N° 575/2013 came into force on 1st January 2021 in Italy.
[3] The materiality threshold is set at: (i) EUR 100 for retail exposures and EUR 500 for non-retail exposures (absolute threshold); (ii) 1% of the total exposure to the counterparty (relative threshold).

Major Rating Agencies Rating Guide for Long and Short Term Debt

Moody's Long Term	Moody's Short Term	S&P Long Term	S&P Short Term	Fitch Long Term	Fitch Short Term	Risk Characteristic
Aaa	P-1	AAA	A-1+	AAA	F1+	Prime
Aa1		AA+		AA+		High Grade
Aa2		AA		AA		
Aa3		AA-		AA-		
A1		A+	A-1	A+	F1	Upper Medium Grade
A2		A		A		
A3	P-2	A-	A-2	A-	F2	Lower Medium Grade
Baa1		BBB+		BBB+		
Baa2	P-3	BBB	A-3	BBB	F3	
Baa3		BBB-		BBB-		
Ba1	Not Prime	BB+	B	BB+	B	Non-investment grade speculative
Ba2		BB		BB		
Ba3		BB-		BB-		
B1		B+		B+		Highly Speculative
B2		B		B		
B3		B-		B-		
Caa1		CCC+	C	CCC	C	Substantial Risks
Caa2		CCC				Extremely Speculative
Caa3		CCC-				In default with little prospect for recovery
Ca		CC				
		C				
C		D	/	DDD	/	In default
/				DD		
/				D		

Investment-grade

High yield

Figure 1.4 - Major agencies' bond rating categories

Table 1.1 shows the historical average default rates by rating category over several investment horizons elaborated by Moody's for the period between 2018 and 2020. These data are relevant not only to investigate the historical performance but also to predict forthcoming default rates. For instance, a portfolio of Aaa-rated securities defaulted at a 0.02 per cent average rate between 1983 and 2020 (over a five years' time horizon). This historical data is also the best estimate of the bond's default risk for investors that are assessing (at the present date) to undertake a five years' Aaa-rated security.

It is easy to note that default rates increase hugely going down to the non-investment grade section, where Caa1 bonds have a default probability of 27.00 per cent over five years. Understanding the gap elapsing between rating categories is important to give the context to the risk premium required by investors that buy sub-investment grade securities. S&P Global Ratings Research's insights on the matter confirm the existence of a strong correlation between rating classes and defaults: the lower the rating, the higher the observed frequency of default (table 1.1), the higher the remuneration of the risk required by investors.

As estimated by Altman et al. (2019), in 2018 high yield securities amounted to $1,656 billion, accounting for 22 per cent of the North American corporate bond market, which itself has been steadily increasing from the late ’90 until nowadays.

Rating/Horizon	1	2	3	4	5	6	7	8	9	10
Aaa	0,00%	0,02%	0,02%	0,02%	0,02%	0,02%	0,02%	0,02%	0,02%	0,02%
Aa1	0,00%	0,00%	0,00%	0,00%	0,02%	0,08%	0,08%	0,08%	0,11%	0,19%
Aa2	0,00%	0,01%	0,13%	0,26%	0,35%	0,44%	0,54%	0,65%	0,79%	0,92%
Aa3	0,05%	0,12%	0,17%	0,25%	0,39%	0,55%	0,77%	0,95%	1,08%	1,20%
A1	0,09%	0,21%	0,37%	0,56%	0,79%	1,04%	1,25%	1,46%	1,64%	1,84%
A2	0,06%	0,18%	0,37%	0,54%	0,76%	1,11%	1,47%	1,84%	2,27%	2,78%
A3	0,07%	0,18%	0,38%	0,58%	0,88%	1,10%	1,38%	1,73%	2,10%	2,49%
Baa1	0,12%	0,30%	0,49%	0,70%	0,85%	1,09%	1,32%	1,60%	1,92%	2,30%
Baa2	0,16%	0,35%	0,56%	0,80%	1,02%	1,25%	1,49%	1,72%	2,01%	2,28%
Baa3	0,23%	0,56%	0,97%	1,41%	1,92%	2,38%	2,82%	3,37%	3,91%	4,53%
Ba1	0,29%	1,11%	1,96%	2,73%	3,64%	4,47%	5,18%	5,83%	6,59%	7,45%
Ba2	0,62%	1,50%	2,59%	3,74%	4,96%	5,92%	6,94%	8,26%	9,69%	11,20%
Ba3	0,83%	2,32%	4,05%	6,10%	7,68%	9,35%	11,18%	13,07%	14,90%	16,69%
B1	1,18%	3,68%	6,44%	9,21%	11,66%	13,76%	15,87%	17,93%	19,86%	21,66%
B2	2,68%	7,02%	11,65%	16,06%	19,62%	22,77%	25,30%	27,42%	29,73%	31,96%
B3	3,48%	8,66%	14,40%	19,34%	23,55%	27,08%	30,08%	33,09%	36,00%	38,37%
Caa1	4,40%	10,37%	16,24%	21,78%	27,00%	31,53%	35,25%	38,37%	41,51%	44,22%
Caa2	8,10%	15,85%	22,99%	29,23%	34,81%	39,88%	44,30%	48,48%	52,12%	54,61%
Caa3	19,57%	33,03%	41,94%	47,87%	52,66%	56,64%	59,78%	62,57%	63,68%	64,71%
Ca-C	36,90%	50,09%	59,10%	65,93%	69,13%	70,23%	72,14%	73,62%	74,75%	75,29%
All	1,80%	3,57%	5,18%	6,55%	7,66%	8,59%	9,37%	10,10%	10,80%	11,45%

Table 1.1 - Average cumulative issuer-weighted global default rate, 1998-2020.

Source: Moody’s investors Service

1.6.3 Default and returns

Default and default loss expectations are the most crucial variables for investors that trade high yield and high-risk corporate bonds (Altman et al., 2019). When exploring the relationship between default rates and economic recessions, Altman shows evidence that corporate default rates tend to peak at the end of the downturn and oftentimes even soon after the recession period ends. Moreover, it can be noticed from figure 1.5 that default rates start rising two/three years before the recession begins (the periods of downturns are highlighted in yellow), for instance before the recessions of 7/90–3/91, 4/01–12/01. However, this was not the case when the crisis of 12/07–6/09 arose, because corporate default rates were mainly aligned with the economic downturn and for sure it was not the case when the Covid-19 crash hit the market, in fact as we can observe from figure 1.5 starting from 2017 until 2019 corporate default rates were decreasing.

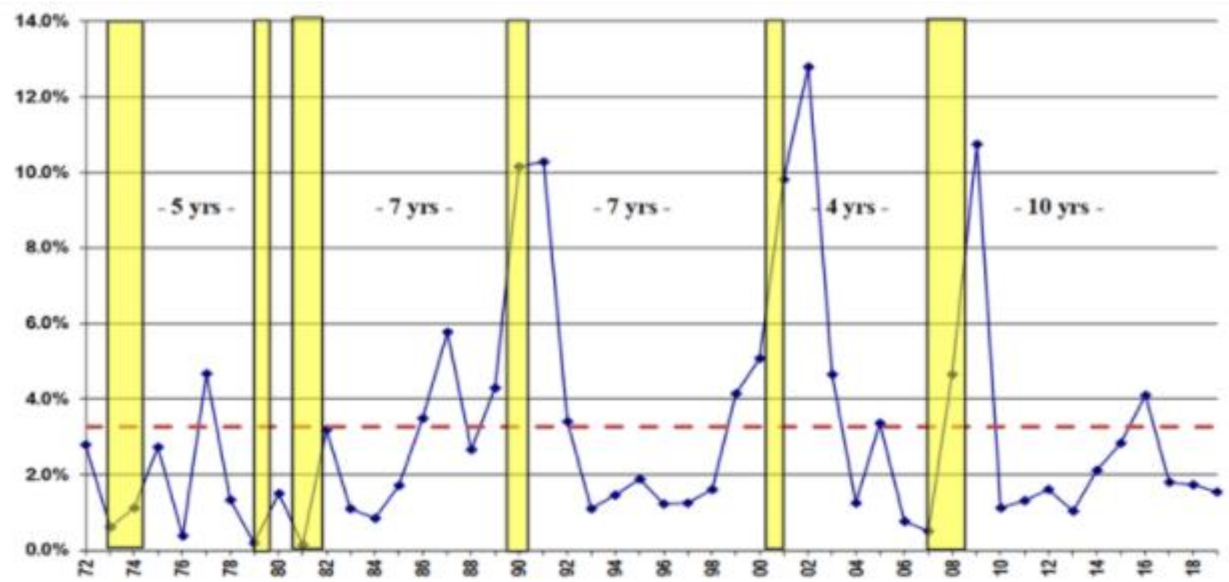

Figure 1.5 - Historical Default Rates and Recession Periods in the United States. High-Yield Bond Market, 1972–2Q 2019.

Sources: E. Altman (NYU Salomon Center) and National Bureau of Economic Research.

In 2019, due to the monetary policies adopted by central banks, the exit of distressed companies from the market, and the benign credit cycle (Moscatelli, 2019), the default rates were as low as 0.06 per cent for investment-grade bonds and 2.45 per cent for speculative-grade bonds.[4]

The Covid-19 pandemic led to one of the broadest recessions since the Great Depression. As demonstrated previously, downturns periods include, or are followed shortly by, strong increases in corporate defaults. Rating agencies explain that during the global crisis triggered by Covid-19 defaults increased, but to an inferior extent than recent recessions. Corporate downgrades also increased, to near a record high. However, in both instances, corporate defaults and downgrades were mainly restricted to the riskier rating classes, resulting overall in good rating performance in 2020. For this reason, despite the severity of the 2020 downturn, this default cycle is expected to peak at a lower rate than the rates observed during the last three recessions. To put things in perspective, Moody's trailing 12-month global default rate for speculative-grade financial and nonfinancial businesses jumped from 3.2 per cent at the end of 2019 to 6.7 per cent at the end of 2020, whereas rated corporate issuers' defaults increased from 105 in 2019 to 211 in 2020. When the Covid-19 crisis hit, central banks reacted quickly injecting liquidity and backed junk companies that raised money on

[4] Global Corporate Default Summary by S&P Global

the credit markets. Thanks to this support by governments and central banks, corporate defaults did not reach the level of the 2009 recession, when 284 rated companies defaulted. According to Moody's estimates, around $234 billion of debt defaulted in 2020 versus a total of $119 billion in 2019, which happened not only due to the rise in the number of default events but also due to the impact of mega-defaults[5].

[5] Mega-defaults are default events that involve over $1 billion of debt

Chapter 2

2. THE VALUATION OF STRESSED AND DISTRESSED COMPANIES

The subsequent section depicts the methodologies useful to evaluate companies with a medium to high risk of insolvency (sub-investment grade credit rating). As shown by figure 1.4, obligations rated below the B class are considered speculative, and are subject to high credit risk. The companies that fall within this category are likely to have sufficient asset quality, although fleeting liquidity crunch, high leverage, oftentimes managerial shortcomings in the product positioning, and poor market penetration.

The cost of equity conventionally used by valuation methods does not reflect the proper credit risk of subjects, since it resorts to the leverage ratio (Debt/Equity) as a proxy of credit riskiness (Capital Asset Pricing Model), without considering the default probability. This approximation works perfectly in the case of investment-grade companies, which have a negligible default probability (see Table 1.1). On the other hand, when evaluating high-yield companies, which can have a default probability as high as 75.29 per cent (10 years average cumulative default rate for Ca-C- rated companies), neglecting to account for credit risk becomes unbearable. Nevertheless, the correct identification and estimation of the credit risk should precede the firm's economic capital evaluation process, to firstly assess the long-term insolvency probability and define the firm's status and choose the most appropriate valuation method (Zanda *et al.*, 2013).
Sub-investment grade firms are frequently close to distress and tracking down the line between going concern and gone concern may be challenging.

2.1 Definition of distress

There is not one unique definition of distress however it is common to begin by distinguishing between financial and operational distress. Financial distress can be detected when a company does not honor its obligations towards creditors, whereas economic distress is triggered by operational inefficiencies and does not have a direct connection with the level of leverage (Senbet & Wang, 2012). Financial distress and the lack of access to capital markets can cause operational distress, but this is not always the case, and even all-equity companies, which do not owe to creditors, can face operational disruption, and ultimately, negative operating margins. The decline in product demand or the profitability deterioration, which usually explains operational lapse, may be associated with non-recurring events, such as regression periods, or even to persistent problems for instance bad management, organizational inefficiencies, or high turnover.

The focus of this chapter is financial distress, as defined by (Damodaran, 2010). The renowned Professor points out that if are consider distressed only the companies that filed for Chapter 11 protection, rather few publicly traded firms will fall within this category. However, if we define distress more broadly as companies that struggle to reimburse interest payments and to fulfill other contractual commitments, distress is far more common. Indeed, Vulpiani (2014) specifies that financial distress can be detected when the company's debt and equity values reflect the potential or likelihood of default or liquidation scenarios.

Nevertheless, the financial and/or operational disequilibrium that triggers the company's crisis is considered an out-of-ordinary event, which has significant implications on valuation methods, due to the following crucial issues:

- uncertainty in the estimation of future cash flows
- higher difficulty in the estimation of the riskiness
- impossibility to take advantage of historical performance data because they are indicative only if standard efficiency levels hold.

In conclusion, it is a good practice to carefully assess the degree and the severity of the company's crisis and its recovery prospects. Thus, before diving into the valuation process, we should take time to analyze the distress peculiarities.

2.2 Causes of decline and fundamental analysis

Evaluating the causes of decline can be useful to estimate the crisis' degree of recoverability. From this standpoint, the fundamental analysis should be the square one to examine the crisis' grounds. Generally speaking, the causes of distress can be occasional or structural, while in the first matter there are good chances of restructuring and implementing a turnaround process to emerge from the tough situation, when the issues have a structural nature, exit the crisis phase can be extremely more challenging. The fundamental analysis' objective is to determine and appraise the causes, such as the global context and the specific factors, that led to a situation of financial distress. It is important to pay particular attention to the following issues:

- In-depth analysis of the factors that negatively influence the performance (industry-related, organizational specific, and/or managerial)
- Assessment of the severity of losses
- Review of the historical trend and structure of losses

At its broadest definition, the fundamental analysis is a stock valuation method that checks both financial and economic analysis to forecast stock prices movements (Reedy, 2012). The process of fundamental analysis involves examining the firms' fundamental financial position through key ratios to assess its financial health with the aim to estimate the stock value and how the stock is valued by the market (undervalued/overvalued). Indeed, the fundamental data examined in the process span from financial indicators to non-financial data such as estimations of demand growth, industry trends, changes in the target market, and potential changes in public policies. The first step to estimate the intrinsic value is to assess the current and future status of the global economy. After that, it is possible to proceed with the analysis of the specific company. In particular, the factors to investigate further are the core competencies and fundamental strengths which can generate a competitive advantage for the firm, such as management skills, performance history, development potential, low production costs, brand allure, etc.

When applying the fundamental analysis to assess whether to invest in stressed or distressed companies enduring a process of turnaround it is crucial to look for financial, competitive, and structural factors that suggest a temporary nature of the crisis, as suggested by Olstein Funds research. Investing in this type of target company can be particularly risky because even if the firm is able to reestablish a positive performance path after a decline period, nevertheless its stock can be penalized by negative market psychology.

Moreover, when assessing to invest in a troubled company, the first thing to evaluate is if the firm has a sufficient probability to succeed in the turnaround process, thus being able to restore sustainable free cash flow and create value for shareholders. Olstein Funds research identifies as firm-specific success factors the following:

- The core business: Does the firm have a sound core business and a sustainable competitive advantage? The turnaround process will be able to restructure the company only if it is struggling with temporary demand setbacks, whereas if the decline has caused irreversible damage to the core business there is no room for turnaround.

- The balance sheet: Is the balance sheet sound enough to withstand a turnaround period?
- Clean accounts: Is the management trying to cover up the true depth of distress?
- What went wrong: How severe is the company crisis? Are the problems correlated to structural factors or are triggered by external agents?
- Management quality: How great are management's decision-making skills and leadership?
- Free cash flows: Is the management team able to make the correct investments to revitalize the cash flow streams? Cash flows are crucial for stressed companies because they are used to cover the debt expenses and avoid default. Thus, the management should prioritize investments that would help operations to generate positive and stable free cash flow.

On the contrary, some factors can decrease the chances of realizing a successful turnaround process, because they raise the risk/reward proportion to an unbearable level and are potentially a value trap. Indeed, some of the red flags to watch for are:

- Poor corporate governance: Is the corporate governance structure strong? Are financial statements and accounting transparent?
- Ineffective management: Is the management team competent and ready to change? The management team should be assessed according to their contribution to the firm's declining path, their leadership skills, and their expertise.
- Multiple turnarounds: Has turnaround been attempted before? Failed previous attempts may conceal structural issues harder to fix.
- Insufficient budget: Is there availability of financial resources to finance the turnaround process? The firm must be ready to unlock all available resources and undertake cash flow improvements, debt restructuring, working capital changes, and cost reduction efforts.
- Weak core business: Are the firm's products and services relevant to the market?

2.3 Going concern vs. gone concern

What are the potential consequences of financial distress? The companies that cannot reimburse their debt obligations on a clear-cut basis, will be forced to liquidate their assets at cut-rate prices to repay their debts. The remaining cash after all creditors have been paid back (if there is any), is then distributed to the company’s shareholders. These “liquidation costs” are deemed direct costs of bankruptcy, and often discourage companies to pursue the liquidation path. Indeed, Damodaran (2010) emphasizes the fact that the costs to bear when a company enters the gone concern stage stretch far beyond the legal costs of bankruptcy and liquidation. In fact, distress can damage severely a firm’s operations, if it alarms the stakeholders such as employees, clients, suppliers, and creditors. In the long term, the companies perceived as distressed are more likely to lose streams of revenues, have higher employee turnover, and bear unfair terms from suppliers than healthy firms. These indirect bankruptcy costs can harm harshly companies that are already struggling.

Thus, whenever the value of continuing operations is higher than the estimated liquidation proceeds and the management decides to restructure the company, it is important to preserve the going concern requisite, exploiting existing assets, resources, and skills, with the aim to navigate through the storm and exit from the crisis.

Further, when facing financial distress, the company should keep all its options open. Indeed, Buttignon (2015) points out that when trying to weather the storm of a crisis, the going-concern capital value estimated in the turnaround plan presented by current management and shareholders should constantly be compared with the value arising from other viable options, namely:

- The going-concern value that new owners would bring to the ownership structure through a change of control while keeping the existing asset base fixed
- The going-concern value that would arise from the combination with other entities through the exploitation of synergies
- The regular check of the liquidation value emerging from the individual sale of the firms’ assets.

Once the existence of the going concern value requirement has been checked it is the moment to choose the appropriate valuation method.

2.4 Valuation methods

The topic of this dissertation gravitates around “junk companies”, defined as firms with a medium to high risk of insolvency, thus ranked in the sub-investment grade rating category. Indeed, before describing the best valuation methods to apply in a distressed context, it can be useful to analyze why traditional valuation methods are inadequate.

Firstly, it is worthwhile to note that standard cost of equity models such as the CAPM, and discounted cash flow models, are based on the implicit assumption that the firm operates as a going concern and has a potentially infinite life. The terminal value is typically calculated assuming a constant and perpetual growth rate of earnings as well. Indeed, the beta used in the CAPM does not reflect properly the credit risk and does not have a significant correlation to the credit rating.

$$\text{(CAPM): Cost of equity} = \text{Risk-free Rate} + \text{Equity Risk Premium (ERP)}$$

$$\text{ERP} = \beta * (r_m - r_f)$$

To adjust the beta for credit risk, the Hamada equation[6] draws upon the Modigliani-Miller theorem and the CAPM method on capital structure and enables the cost of equity estimation to also reflect the financial leverage effect on firms. The underlying assumption is that the debt on equity ratio is a good estimator for the credit risk. Nevertheless, the Hamada equation provides a linear correction to include the debt weight on capital structure but is designed for the low and ordinary credit risk levels of healthy publicly traded companies and is not effective in accounting for the credit risk profile of stressed and distressed companies.
As stated by Damodaran (2010), considering the likelihood and the potential consequences of financial distress, it seems irresponsible to ignore this prospect in the process of valuing a firm, especially when the specific company has a history of poor financial health and has built up a considerable amount of debt obligations.

2.4.1 Discounted cash flow valuation

The failure to account properly for the possibility of distress when evaluating sub-investment grade companies can lead to skewed upward estimations of the firm's current value. Indeed, in presence of high distress likelihood, constrained access to capital, and low revenue streams compared to the historical trend, the discounted cash flow valuation method will probably overestimate cash flows and the enterprise value.

To incorporate the potential effects of distress in both expected cash flows and discount rates, this section will describe a modified version of the discounted cash flow model (Damodaran, 2010).

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[6] $\beta_L = \beta_U [1+(1-T)(D/E)]$
βL=Levered beta
βU=Unlevered beta
T=Tax rate
D/E=Debt to equity ratio

Firstly, to correct the assumption that expected cash flows are infinite, multiple scenarios – ranging from the most pessimistic (default) to the most optimistic (infinite life) – are incorporated in the expected cash flow formula, where probabilities (π_{jt}) and cash flows are estimated each year (t) and are assigned to each possible scenario (j), resulting in the following estimation:

$$\text{Expected cash flow} = \sum_{j=1}^{j=n} \pi_{jt} \text{ (Cash Flow}_{jt}\text{)}$$

π_{jt} = probability of scenario (j) at time (t).

Cash flow_{jt} = the cash flow estimated under scenario (j) at time (t).

The probabilities and the expected cash flows are estimated for every year of the business plan because they are likely to undergo changes from year to year.
This approach can be complex to implement because estimating probabilities of distress for each scenario and each year of the forecasted period is not an easy task. Nevertheless, in the next paragraph, we present the discount factors to be used to discount expected cash flows.

2.4.2 The estimation of discount rates

The inadequacy of standard methods to evaluate the cost of equity of stressed and distressed companies was highlighted in the first paragraph of this chapter. Now there will be proposed some alternative approaches to calculate discount rates that account for the companies' true distress risk, following the approach of Damodaran (2010).

The first proposal to adjust the cost of equity for the true firm's risk is to use bottom-up unlevered betas along with the company's debt on equity ratio (Hamada correction).
Bottom-up betas are estimated breaking the specific company object of valuation down into the diverse businesses in which it operates. Thus, the fundamental risk (unlevered beta) of each business is estimated and the weighted average of these risks is the bottom-up beta. To assess the unlevered (asset) beta for each business we identify comparable firms first, then make an average of their regression betas and un-lever them. The resulting bottom-up beta is more precise than the regression beta commonly used in the CAPM and reflects the business mix of the company. Indeed, given the fact that usually distressed companies have a high level of the debt on equity ratio (the equity diminishes due to a drop of stock prices) and cannot benefit from the tax shield (loss-making companies), levered betas are considerably higher than regression betas.

$$\text{Levered Beta} = \text{Bottom-Up Unlevered Beta } [1 + (1 - \text{T}) * (\text{D/E})]$$

Moreover, to compute the correct cost of equity, it is necessary to estimate the proper debt on equity ratio. For the first year, it is possible to use the current market debt on equity ratio, but for the following years, it should be estimated based on the expected improvements in profitability, thus progressively reducing it. Usually, a target debt on equity ratio based on the industry average is used for the whole valuation period, however, this is not a good practice because it can lead to incorrect estimations of the company's value if it has a critical debt level.

An alternative way to estimate the cost of equity consists of employing a beta that reflects a healthy firm in the same industry (comparable) and then add a distress premium:

$$\text{Cost of Equity} = \text{Risk-free Rate} + \text{Healthy Comparable Beta (ERP)} + \text{Distress Premium}$$

The distress premium can be computed either by taking as a reference historical data on returns gained by investing in the equity market of distressed companies or comparing the firm's pre-tax cost of debt to the average cost of debt of its industry.
The cost of debt can be adjusted for distress using default spreads estimated by the company's credit rating (default spread).

$$\text{Pre-Tax Cost of Debt} = \text{Risk-Free Rate} + \text{Default Spread}$$

If the company is not rated by an external rating agency, internal or synthetic credit rating models can be employed.

2.4.3 Focus on sub-investment grade firms

The sub-investment grade credit market is becoming increasingly relevant. S&P estimates that high-yield-rated debt grew by 4 per cent from 2018 to 2019 in the US and amounted to $2.6 trillion as of January 1st, 2019. Indeed, in 2018 US investment-grade debt amount raised by about 3 per cent to a total of $6.7 trillion. Thus, speculative-grade debt accounts for a total of 28 per cent of the American corporate debt market, making sub-investment grade firms a burning topic.
The correct estimation of the credit risk premium becomes an essential prerequisite when evaluating sub-investment grade companies. Indeed, debt repayment ability depends on the firms' cash flow generation, which can be insufficient and/or unstable for high yield companies, triggering high credit risk levels.

This paragraph will describe the process of risk premium estimation, according to the methodology developed by Oricchio (2012) and Zanda *et al.* (2013) based on the following steps:

1. Estimation of shareholders' expected loss (default probability (PD) and loss given default)
2. Determination of risk-adjusted spread through the junior subordinated pricing model
3. Integration of CAPM and Fixed Income Approach for the estimation of risk premium (IPM)

2.4.3.1 The estimation of the shareholders' expected loss

The estimation of shareholders' expected loss applying the Fixed Income Approach (FIA) involves the assessment of the expected loss of both a part and the whole capital invested, starting from the estimation of expected loss for debt holders and then moving to the expected loss for shareholders.
In the case of public companies, the expected credit loss rates are provided by rating agencies (see table 2.1). It is worthwhile to specify that when debt holders incur a loss the loss given default is equal to 100 per cent of equity (equity is subordinated with respect to senior debt). Indeed, credit rating models are indirectly estimating the probability that shareholders lose 100 per cent of their equity.

$$\text{Credit risk premium} \approx \text{PD} * \text{debt loss given default}$$

$$\text{Equity risk premium} \approx \text{PD} * \text{equity loss given default}$$

Rating\Horizon(Year)	1	2	3	4	5
Aaa**		0,01%	0,01%	0,02%	0,04%
Aa	0,01%	0,04%	0,07%	0,12%	0,19%
A	0,03%	0,10%	0,21%	0,33%	0,47%
Baa	0,10%	0,25%	0,43%	0,65%	0,88%
Ba	0,52%	1,46%	2,58%	3,77%	4,84%
B	2,00%	4,82%	7,75%	10,42%	12,83%
Caa_C	6,12%	10,98%	15,16%	18,80%	21,97%
IG	0,05%	0,14%	0,26%	0,39%	0,54%
SG	2,63%	5,32%	7,89%	10,19%	12,19%
All Ratings	1,05%	2,09%	3,06%	3,89%	4,59%

Table 2.1 - Average cumulative credit loss rates by letter rating, 1983-2020[7].

Source: Moody's Investors Service

To include the possibility that shareholders suffer only a partial loss of capital invested, it is estimated the possibility that the loss given default is infinitesimal. Firstly, when financial debt increases in

[7] Based on average default rates and senior unsecured bond recoveries measured on issuer-weighted basis.

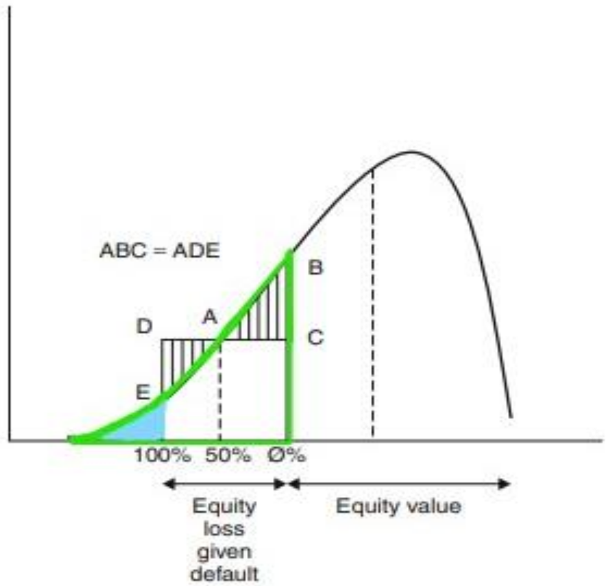
proportion to equity, the firm's default probability increases significantly. At the limit, if the firm were financed only with debt, senior debt default probability would match equity default probability.

$$\text{PD equity} > \text{PD debt}$$

$$\lim_{\frac{D}{(D+E)} \to 1} \text{PD debt} \rightarrow \text{PD equity}$$

Thus, to consider both the maximum and the minimum limits of loss given default, the equity risk premium can be computed as the sum of probability of default floor (credit loss probability) and an average loss given default of 50% for the 100–0% loss given default range (range between an infinitesimal and a 100% loss). Indeed, the assumption behind this estimation is that the area of overestimation of the loss given default of the 100–50% range (DAE) is comparable to the area of underestimation of the loss given default of the 50–0% range (ABC), as shown in figure 2.1.
In conclusion, the risk premium is determined as follows:

$$\text{Equity risk premium} \approx \text{PD cap} + 50\% \ (\text{PD cap} - \text{PD floor})$$



Probability of default floor (Light blue): Probability that shareholders suffer a loss greater than 100 per cent of equity.

Probability of default cap (Green): Probability that shareholders suffer at least an infinitesimal of equity.

Figure 2.1 - Over-estimation error and under-estimation error

Source: Oricchio (2012)

2.4.3.2 Junior subordinated pricing model

In the previous paragraph the liability side of the balance sheet was treated as it were structured debt, identifying equity as a junior tranche (subordinated debt) and financial debts (borrowings from the bank) as senior tranches. In this context, equity can be assessed through the junior subordinated notes' pricing method. The resulting risk-adjusted spread is the risk premium of equity, which accounts not only for the probability of default, but also for the probability of survival.

$$(1 + \text{i BTP}) = \text{PD equity} * \text{loss given default equity} + (1 - \text{survival probability}) * (1 + \text{i BTP} + \text{i}_2)$$

$$\text{i}_2 = \frac{\big((\text{PD equity} * \text{LGD equity}) + \text{survival probability}(\,1 + i\ \text{BTP})\big)}{(1 - \text{survival probability})}$$

i_2 = Equity risk premium
i BTP = BTP long term interest rate
PD equity = Default probability for shareholders

2.4.3.3 Integrated pricing model (IPM)

The Fixed Income Approach (FIA) just outlined estimates the equity risk premium based on shareholders' loss given default, by using the junior subordinated notes pricing model. This approach is particularly convenient because it reflects the credit risk estimated by the rating agencies for each credit rating class. Indeed, as mentioned above, this method allows to overcome the lack of CAPM to estimate properly the credit risk. Nevertheless, this model has merit up to a point as well. In fact, the Fixed Income Approach does not account properly for the market risk, especially when it is used to valuate investment grade companies.

Thus, generally the CAPM is used to estimate the equity risk premium of firms with low credit risk (investment grade), whereas the Fixed Income Approach (FIA) is employed to assess the equity risk premium of companies with high credit risk (non-investment grade).
Further, a very adaptable model to weight strengths and weaknesses of both the CAPM and FIA is the Integrated pricing model (IPM). The IPM implies to compute the equity risk premium as the sum of risk-free rate and the maximum equity risk premium (ERP) coming eighter from the CAPM or the FIA.

$$\text{Cost of equity} = \text{Risk-free Rate} + \text{Equity Risk Premium (ERP)}$$

$$\text{Equity risk premium (ERP)} = \max\,(\text{CAPM, FIA})$$

2.4.4 Dealing with distress separately

A valuable alternative to the approaches aforementioned is to deal with distress separately, according to a methodology developed by Damodaran (2010). This method involves to ideally separate the valuation of the company supposing that the going concern assumptions hold, from the potential value arising from the concretization of distress, thus if the company is to enter the gone concern phase. The square one to assess the potential effects of distress is to evaluate the cumulative probability of the company becoming distressed over the period forecasted and the expected proceeds resulting from the ultimate sale. The firm value can be formulated as:

$$\text{Firm Value} = \text{Going-Concern DCF} * (1 - \pi\ \text{Distress}) + \text{Distress Sale Proceeds} * \pi\ \text{Distress}$$

This approach boasts a simple valuation process and enables to make sound assumptions in relation to both the going concern and the gone concern alternatives. Distress practitioners are used to evaluate deeply distressed firms through the liquidation approach. Indeed, the distress value to which we are referring in the above formula tends to the liquidation value at the limit (when the probability of distress is 100 per cent the two values are equal). However, for the purpose of this dissertation, the distress value approach is preferred because it leaves the way open to the chance (even remote) that the company maintains or regains the going concern premise.

2.4.4.1 Going concern Discounted Cash Flows (DCF)

The going concern assumption implies that the company remains active. Given that cash flows are estimated only for the scenarios where the firm stays alive, the arising outcome should exceed the expected cash flow of the modified DCF method. Within this framework, it is necessary to set the correct assumptions to reflect the going concern supposition. For instance, the cost of debt will diminish through the years as the company reduces its debt overhang, and as soon as the net income returns positive the firm can benefit from tax shield savings previously accrued. The majority of DCF valuations are implicitly going concern valuation because they assume constant and infinite cash flows, as was mentioned in the introduction.

2.4.4.2 The probability of distress

To evaluate the potential effects of distress, this method involves the assessment of the cumulative probability of the company becoming distressed over the period forecasted (π_{Distress}). There are three main alternatives to estimate the probability of distress. The first path includes statistically estimating the distress probability through a comparison between the company's peculiarities (such as profitability, size, credit risk) and the observable characteristics of a statistic sample composed of both companies that filed for bankruptcy in prior years and companies that remained active. The second approach involves evaluating the distress probability through bond ratings and default rates provided by rating agencies. The third and last methodology entails using the company's bonds to evaluate the distress probability.

1) Statistical approach:

Every year lots of companies incur default or bankruptcy, as described in the first chapter of this dissertation, thus providing a generous database with the potential reasons that led to the apotheosis of distress and plenty of data to estimate the likelihood of forthcoming bankruptcy events.
One of the first scholars to build a statistical method (which is still relevant up to date) has been Altman, who came up with an indicator named Z score. Altman (1968) assembled the first formulation of the Z score starting from five financial indicators, which are reported below.

$$\text{Z Score} = 0.012\ \text{X1} + 0.014\ \text{X2} + 0.033\ \text{X3} + 0.006\ \text{X4} + 0.999\ \text{X5}$$

X_1 = Working capital/Total assets
X_2 = Retained Earnings/Total assets
X_3 = EBIT/Total assets
X_4= Market capitalization/Book value of total debt
X_5 = Sales/Total assets

The strength of this methodology consists in the fact that four of the five variables require data from one single financial statement and only one requires equity market figures (X_4). Moreover, the original model just described revealed an outstanding sample accuracy of Type I (predicting bankruptcy events) and Type II (predicting non-bankruptcy cases) (Altman, 2018). The Z score is useful to classify if a firm is likely to incur bankruptcy or not. Indeed, the distinction was based on cutoff scores. A company with a Z score greater that 2.99 was considered safe, whereas firms with scores lower than 1.81 were distressed, leaving the intermediate range as a grey zone.

Notwithstanding its usefulness to forecast bankruptcy, an analysis based on a linear discriminant does not yield the bankruptcy probability needed to implement the model selected (π_{Distress}). For achieving the distress probability, it can be useful to implement a probit model. A probit model is a statistical regression wherein the dependent variable can assume only two outputs (0 or 1). The objective of the probit approach is to evaluate the probability that an observation will fall into one of the two predetermined categories. In this context, starting from the same data sample of the linear analysis above-mentioned, it is possible to use the probit to estimate the probability that the company either survives or file for bankruptcy in a time frame. Indeed, the indicator variable will be a Dummy assuming the value of 1 if the company survives or 0 if the company incur bankruptcy.

$$\text{Distress Dummy } \begin{cases} 1 \rightarrow \text{the company remains active} \\ 0 \rightarrow \text{the company goes bankrupt} \end{cases}$$

At this point, it is possible to examine all the information that was already available at the beginning of the observation period and that may have allowed a correct separation between the companies that remained active from the ones that did not. Some variables that can be tested are financial ratios such as debt on equity, cash flow indicators and operating margins. Thus, the distress dummy variable can be used as dependent variable and financial ratios as independent variables. In conclusion, if the probit method reveals a statistically and economically significant relationship between the financial input and the output (distress), there is a sound basis to estimate the probability of bankruptcy.

2) Approach based on credit rating:

This second method consists of gathering information about firms' default probabilities from the data that credit rating agencies provide to investors. Since bond ratings are available for many companies (especially in North America), lots of data can be collected and it can be particularly useful to analyze the historical default rates, because they are a good estimation for the expected default probabilities (see paragraph 1.6.2). Granted that the rating process and standards have remained rather stable through the years, default probabilities can be used as inputs in the DCF formula (π_{Distress}). The data about default rates are provided by rating agencies according to their own estimations (see Table 1.1 paragraph 1.6.2).

This approach is quite straightforward, but it is based on the assumption that rating agencies are doing a good job in estimating default probabilities and that they do not change rating standards over time. Moreover, the definition of default does not implicate that the company goes out of business and shuts down (see paragraph 1.6.1), on the contrary, as a matter of fact, many companies are able to resume their operations as going concern businesses after a default event.

3) Bond price approach:

Usually, the bond price reflects the default spread within the cost of debt that is used to discount cash flows. However, if we discount the expected cash flows at the risk-free rate, we can separate the distress probability (which is incorporated in the cost of debt). Assuming that the annual probability of default is constant, the price of the bond can be formulated as follows:

$$\text{Bond Price}^{8} = \sum_{t=1}^{t=N} \left[\frac{\text{Coupon }(1-\pi\text{ Distress})^{t}}{(1+rf\ rate)^{t}}\right] + \left[\frac{\text{Face value of the bond }(1-\pi\text{ Distress})^{N}}{(1+rf\ rate)^{N}}\right]$$

Indeed, starting from this equation we can use the price at which the bond is traded on the market to extrapolate the probability of distress, obtaining the annualized default probability of the bond until its maturity. This method is quite simple to implement if the bond is publicly traded, but it implies a series of simplifying assumptions, thus the distress probability can be slightly inaccurate.

2.4.4.3 The estimation of distress sale proceeds

If the company is not able to timely repay its debt obligations and defaults, there are some chances that it will soon cease to exist. In this event, the distressed company will be forced to sell its assets at a cut rate with respect to the present value of expected cash flows arising from both existing assets and planned investments. The expected distress sale proceeds can be estimated as follows:

1. Estimation of the value that can be recovered as a percentage of the expected cash flows assessed through the standard DCF (assuming that it will be lower than 100%)
2. Estimation of the present value of cash flows arising from current activities (without accounting for planned investments).
3. Estimation of distressed sale proceeds as a percentage of assets' book value, taking as the reference percentage the average proceeds gained by comparable distressed firms.

2.4.5 Adjusted Present Value (APV)

The Adjusted Present Value model calculates the firm's value as the sum of the unlevered enterprise value (theoretical value of the company in the absence of debt) and the present value of the tax shield (theoretical value of the tax benefits determined by the financial debt). When evaluating distressed firms, the potential advantage of splitting the debt from the value of the operating assets is that the probability of distress can be analyzed more carefully.

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[8] Bond with a fixed coupon maturing in N years

The unlevered enterprise value is computed by discounting the free cash flows at the unlevered cost of equity ρ_u[9] and assuming the growth rate (g) is constant.

$$\text{Unlevered Value} = \sum_{t=1}^{N} \frac{CFt}{(1+\rho u)^t} + \left\lfloor \frac{CFn(1+g)}{(\rho u - g)} \right\rfloor * \frac{1}{(1+\rho u)^N}$$

$$\text{Present value of tax shields} = \sum_{t=1}^{N} \frac{(\text{Dt}-1 * \rho\text{d} * \text{t})}{(1+\rho d)^t} + TV\ 10(tax\ shields) * \frac{1}{(1+\rho d)^N}$$

$$\text{Vl} = \text{Vu} + \text{Vts}$$

The tax shield is the present value of income tax savings (taxes reduce the amount of income taxable, thus diminishing interest charges). If the company under valuation is distressed and does not generate operating income, interest charges may exceed the taxable income, therefore operating loss deductions will be carried-forward, and the company will be able to benefit from them once the operating income returns positive.

Vulpiani (2014) proposes that to take account for distress the APV model should be modified as follows:

$$\text{Enterprise value} = \text{Vu} + \text{Vts} - \text{Vdc}$$

$$\text{Vdc} = \text{Present value of net distressed-related costs}$$

To estimate distressed related costs, Damodaran (2010) suggests to start from the assessment of how much the given level of debt impacts on the company's default risk and expected bankruptcy costs. Therefore, the probability of default in presence of additional debt should be estimated together with direct and indirect costs of bankruptcy.

$$\text{Present value of Expected Bankruptcy Cost} = \text{Probability of Bankruptcy} * \text{PV of Bankruptcy Costs}$$

The Enterprise Value of distressed firms is negatively impacted by low tax benefits streams and large estimated bankruptcy costs.

[9] $\rho_u = r_f + \beta_u\ (RP_m)$
ρ_u = Unlevered cost of equity
r_f = Risk-free Rate
β_u= Beta unlevered
RP_m = Market Risk Premium
[10] TV (tax shields) = $D_{T-1} \times t$

2.4.6 Hedge funds

The subjects that more than everyone master distressed valuation methods are hedge funds. Indeed, hedge funds managers that pursue a value-oriented strategy seeking to capitalize on the risk mis-pricings in sub-investment grade credit markets need to master these techniques perfectly to spot the mentioned mis-pricings.

Distressed debt funds are wizards in picking up the bonds of stricken companies that have the highest possibility to thrive. Especially this year, hedge funds seeking to profit from troubled companies enjoyed the greatest returns since the Great Financial Crisis, thanks to the stimulus-driven market rally which raised the price of debt about to default, reaching returns as high as 11.45 in the period January-July 2021 (Wigglesworth, 2021). This marks the best performance in 2021 for all major hedge funds, compared to the other investment strategies, according to Eurekahedge (figure 2.2).

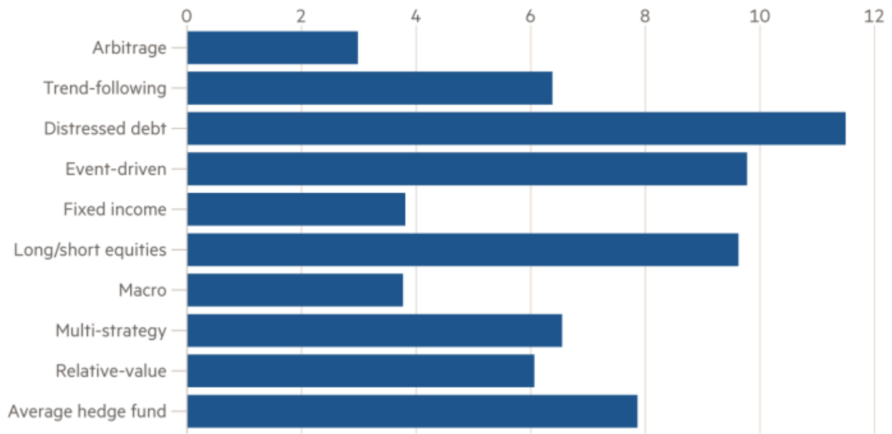

Figure 2.2 - 2021 Hedge funds' returns by strategy (per cent).

Source: ©FT elaboration on Eurekahedge data

Hedge funds are investment partnerships that use mutual funds provided by their investors to invest aggressively in various strategies and gain profits for investors. Distressed hedge funds strategy consists of placing short-term bets on bonds that are close to default or already defaulted offering to firms emergency loans and sometimes even taking control of the target through court appointment.
The potential for hedge funds' profit comes from the fact that they purchase distressed debt (usually bonds), at a very low percentage of their face value. Subsequently, if the formerly distressed firm comes out from insolvency and becomes a profit-making business (restores the going concern), the

hedge fund will sell the firms' bonds for an extremely higher price, making huge returns (Sylvester, 2020). Given the fact that hedge funds will be able to return on their initial investment only if the company increases its market value, it is crucial that they correctly identify the companies that have the potential to be restructured and turned into profitable businesses.

The outperformance enjoyed in 2020 and 2021 by funds that invest in the hardest-hit firms and segments of the economy stems from the positive signals of economic recovery after the pandemic, which has been boosted by central banks' aids and by efforts in the vaccination campaign.

In February (2021), Brian Chappatta published an article on Bloomberg where he argued that the opportunities to invest in distressed debt looked almost squeezed to their limits, meaning that the more lucrative distressed situations had been already exploited in 2020. Chappatta expected that with the improvement of the sanitary situation also the economy would have recovered, wiping out distressed hedge funds' outsized profits. This opinion has been essentially confirmed if we look at data available up to date. The average return of CCC and lower-rated US corporate bonds has dropped from a March 2020 peak of almost 20 per cent to near a record low of about 7 per cent in Q3 2021.
Returns have been fostered by a significant rally across credit markets, which resulted in lower borrowing costs and helped the companies hardest hit by the pandemic crisis, such as cruise lines, hotels, and airlines to raise sufficient funds to weather the storm (Wigglesworth, 2021).

In conclusion, it is important to tackle this topic from the companies' perspective. An excessive enthusiasm in borrowing to mitigate the revenue shortage during the pandemic can result in long-term indebtedness hard to manage, which can limit the range of forthcoming investments. For this reason, it is crucial that companies stay focused on reestablishing their profitability and do not fall into the over-leverage trap (Platt, 2021).

Chapter 3

3. METHODOLOGY

The objective of this study is to identify the drivers of value creation that can be spotted when highly distressed companies undertake a turnaround process and manage to avoid Chapter 11. For this scope, the starting point of the research will be struggling companies. As far as we are aware, there are no studies or researches that focus exclusively on the value creation of sub-investment grade public companies in the literature up to date. The focus is to identify which troubled companies to bet on, based on their intrinsic probability of surviving and becoming profitable again.
This section explains the methodology used to conduct the empirical analysis. The process undertaken to analyze the value creation of sub-investment grade companies is the following:

1. Identification of the data sample
2. Identification of the financial indicators that will be statistically tested as potential drivers of the value creation and first multivariate regression
3. Application of basic descriptive statistics tolls for a first screening of the sample
4. Re-definition of the sample as the probability that a sub-investment grade firm (highly distressed) creates value for shareholders
5. Multivariate regression in two stages to evaluate the variables that significantly influence the value creation and test their predictive ability
6. Univariate regression of the indicators commonly used to assess the default probability (Net debt/EBITDA, ICR, Altman’s score), to test if they are significant to estimate the value creation of distressed companies

The study considers a sample of 146 troubled companies, publicly traded in the European and American capital markets. The observed period spans from 2014 to 2019[11] and includes all firms with non-missing values for the measures chosen to estimate the value creation. The general population of companies has been identified through Bloomberg and Refinitiv databases.

3.1 Sampling criteria

The starting point to identify the companies in a situation of stress and distress has been the high yield credit rating market, as described in paragraph 1.6.2. The underlying assumption behind the decision to identify the companies to include in the sample based on their rating relies on the fact that debt

[11] Market capitalization data have been collected between 31/12/2014 and 31/12/2019.

rating usefulness is to identify the creditworthiness of an issuer concerning a determined debt issue. More importantly, credit ratings are an objective measure of security riskiness and are easily accessible for all investors. Nevertheless, as stated by Singal (2013), credit rating can be used as a tool to assess financial performance, not only because it is backward and forward-looking, but also because credit rating agencies are entities specialized in the information gathering and valuation process, with access even to non-public information (Kisgen, 2006). For these reasons, the focus of this research is on companies with a highly speculative rating, considering them a proxy of all businesses struggling to meet their financial obligations. Indeed, the general population of this analysis includes the securities in the range from B1 to C of Moody's rating scale.

Moreover, to identify all the issuers in the high-yield category during the time frame selected, it has been used the Bloomberg function RATC (rating revision monitor), which displays a list of current and historical credit ratings, enabling to spot upgrades, downgrades, and other changes that reflect the company's financial strength and riskiness. Since the credit rating of senior debt is considered a good proxy of the companies' credit rating, the sample of companies has been built selecting all the issuers with a non-investment long term rating of Ca, Caa3, Caa2, Caa1, B3, B2, and B1 on their senior debt.

Most of the companies in the sample are from North America since the majority of rated issuers are domiciled there.

The industries selected and included in this quantitative analysis are communications, consumer discretionary, consumer staples, energy, real estate, health care, industrials, material, technology, and utilities.[12] On the contrary, financial services (such as banks, asset management funds, insurances, etc.) and governments issuers, which are of no interest for the present research, have been excluded from the preliminary sample.

3.2 Variables construction

To supply at the lack of specific research on the value creation of sub-investment grade companies we test with multiple regression diverse variables that have resulted significant in previous studies on bankruptcy, turnaround, and default probability.

The firm size effect is measured as the market capitalization (*Size*) since this measure allows to capture the firm's growth opportunities and also equity market conditions (Dang *et al.*, 2018). The

[12] The mentioned categories are Bloomberg fields (BICS). BICS for stock companies includes 12 *macro* sectors, which stand for the broadest grouping of general business activities.

variables *MS* (Price/Sales) and *MB* (Price/Book value) have been included cause they are considered good indicators for stock returns (Shabib-ul-hasan et al., 2015). Thus, we have selected a set of accounting-based indicators for the analysis, namely the *ROI, OROIC,* and *ROA* (Serrano-Cinca et al. 2013).

We then included a Cash Flow indicator (*OCF*), with a view to the work of Karas *et al.* (2020), who points out that operating cash flow ratios play a prominent role in financial distress. The Net Debt/EBITDA (*D.EBITDA*) is an indicator widely used by practitioners since it estimates the company's ability to meet its financial obligations.

The variables PD after one year and after six years have been included due to the fact that they are considered an objective measure to assess how likely is the company to incur default.

Finally, we used the Altman's Z score as a variable (*Z*) since the Altman (1968) model is one of the most commonly used to predict bankruptcy and has been previously employed also for researches on turnaround processes (Mckiernan, 2009).

3.2.1 Market capitalization

The method used to estimate the value creation for shareholders is market capitalization, in a perspective of wealth maximization. Market capitalization is defined as the market value of the equity (outstanding shares of stock) at a particular date and depends upon the demand and supply for a particular stock in the equity markets. The market value of equity is calculated by multiplying the firm's total outstanding shares by the market price of a single share on a particular day (normally it is evaluated at the end of the fiscal year). Indeed, market capitalization is a useful approach because it includes diverse elements such as financial efficiency, tangible capital, and intangible assets. A lot of variables are indirectly mirrored by the market capitalization, such as the company's reputation, the brand's image, the product niche, the future expectations in terms of earnings and growth, dividend payout trends, etc. and all of them influence the share price under the assumption of stock market efficiency. The market capitalization increases or decreases day by day the value of the stock according to the company's performance and thus the shareholders will gain or lose on the stock market (Singh *et al*, 2013).

3.2.2 Turnaround definition

There are no hard-and-fast definitions when it comes to defining the peculiarities of turnaround situations. In this context we will use this term to identify the companies whose financial performance indicates a strong distress and a high probability of default in the near future unless short-term corrective actions are implemented (Slatter et al., 1999). As we mentioned above, the criteria to identify the companies in a situation of distress is their own high-yield credit rating. Thus, we will consider that a turnaround process has been actuated if the firm is able to achieve an upgrading during the observation period.

3.2.3 Zombie firms

Zombie firms are defined as companies that do not report profits (net of interest expenses) for several years, thus being unable to cover debt expenses with current profits, and nevertheless continue operating. These companies are considered "distressed", according to financial books' definitions, and are qualified as subjects close to liquidation, yet they are rarely liquidated *de facto* (Hallak et al., 2018).

To set the stage for the following quantitative study here is outlined the OECD definition of a zombie firm, which will be the base of the analysis. Indeed, OECD (McGowan, 2018) defines a company as a zombie if two conditions are met:

- the interest coverage ratio, calculated as the ratio of operating profits (EBIT) to interest payments, is less than one for three consecutive years (t, t-1, t-2).
- the company is 10 years or older.

The coverage ratio is considered a standard measure of loan repayment capacity by credit analysts, and it is used in this context to assess companies' profitability. Indeed, the interest coverage ratio is easily comparable across countries, it is less dependent on productivity than negative profits, and it avoids considering also subsidized credit which can twist the company's real status (McGowan, 2018).

Moreover, considering only mature firms helps to prevent misclassifying as zombie companies that are young and growing, while still struggling with negative operating profits which are common in the first phases of a business.

3.3 Sample analysis

From a first screening of the sample, it can be noted that 61.6 per cent of the 146 companies considered are still active at time t=6, in 2019, for a total of 90 firms. Moreover, 22.6 per cent of the companies sampled were acquired in the time frame between 2014 and 2019, 11 per cent of firms filed for Chapter 11 and were delisted contextually, and the remaining 4.8 per cent of businesses were delisted for strategic reasons.

As it is shown in table 3.1, it is interesting to note that the percentage of companies still active at t=6 is at its maximum for the B1-rated category and decreases scrolling down, according to the worsening of the credit rating. Indeed, the incidence of Chapter 11 filings increases going down to the bottom of the column, demonstrating that as the rating observed at t=0 gets worse, the percentage of Chapter 11 cases at t=6 rises.

Rating at t=0	Acquisition	Active	Chapter 11	Delisted	Total
B1	16%	77%	2%	5%	100%
B2	25%	68%	3%	5%	100%
B3	29%	62%	5%	5%	100%
Caa1	28%	41%	25%	6%	100%
Caa2	20%	40%	40%	0%	100%
Caa3	0%	33%	67%	0%	100%
Ca	0%	0%	100%	0%	100%
Total	**22,6%**	**61,6%**	**11,0%**	**4,8%**	**100%**

Table 3.1 - Status at t=6 divided by rating at t=0.

Further, starting from the 90 companies that remained active during the whole period, 44 (49 per cent) were able to create value for shareholders, registering an increase in the market capitalization (computed as market capitalization at the end minus market capitalization at the beginning). As it is shown in table 3.2, the companies that registered a downgrading in the timeframe between 2014 and 2019, also incurred a decrease in the market capitalization in 76 per cent of cases. Indeed, the firms that obtained an upgrading in the credit rating, accrued a market capitalization increase as well.

Rating change	DECREASE In market cap	%	INCREASE In market cap	%	Total
Downgrading	19	76%	6	24%	100%
Steady	7	54%	6	46%	100%
Upgrading	10	33%	20	67%	100%
WR	10	45%	12	55%	100%
Total	**46**	**51%**	**44**	**49%**	**100%**

Table 3.2 - Variation in market capitalization divided by rating movements classes.

Moreover, taking a closer look at the 44 companies that created value in the period, the narrow sample's average market capitalization increase is 113 per cent, with a median of 74 per cent. It is important to note that these data account for the whole investment-grade class.

Further, by dividing the average market capitalization increase by rating category, it can be observed that a higher credit rating does not assure superior value creation (table 3.3). This implies that rating classes do not have a predictive ability (B1-rated companies do not assure a higher value creation than B2 companies on average), and the research must be carried forward to other potential indicators.

Rating	Average of Δ value creation beg-end
B1	75%
B2	137%
B3	76%
Caa1	241%
Caa2	7%
Caa3	140%
Total	**113%**

Table 3.3 - Value creation divided by rating classes.

3.4 Population dynamics

This paragraph will describe the dynamic of zombie firms, which will be identified according to the definition presented in paragraph 3.2.1. Indeed, the steps followed are:

1) Selection of firms that remained active in the timeframe between 2014 and 2019
2) Selection of companies which are 10 or more years old
3) The division between zombie and non-zombie firms is based on their ICR at time t, t-1, t-2.

81 companies comply with requirements 1) and 2) in the preliminary sample. Now, according to point 3), 67 firms have been identified as non-zombie at the beginning of the observation period (83 per cent) *versus* 14 zombie firms (17 per cent). As reported in table 3.4, of the 67 non-zombie firms at t=0, 41 were still non-Zombie at t=6, 8 transitioned to the zombie status, and 18 were delisted. Indeed, zombie companies at the beginning of the observation remained zombies in 21 per cent of cases, became non-zombies in 43 per cent of the time, and were delisted in 36 per cent of cases.

	Status at the beginning			
Status at the end	**Non-Zombie**	**%**	**Zombie**	**%**
Delisted[13]	18	27%	5	36%
Non-zombie	41	61%	6	43%
Zombie	8	12%	3	21%
Grand Total	**67**	**100%**	**14**	**100%**

Table 3.4 - Zombie firms at t=0 vs their status at t=6.

[13] The category "Delisted" includes acquisitions, Chapter 11, and delisted classes.

Starting from the 14 zombie firms at the beginning of the observation, 9 are still alive at t=6 and 4 of them registered an increase in value (3 out of 4 were even able to exit from the zombie status). As of the 67 non-zombie firms, 26 (39 per cent) show an increase in the market capitalization, 18 (27 per cent) a contraction, and 23 (34 per cent) were delisted.

3.5 Descriptive statistics of value creation

In paragraph 3.4 we analyzed the average value creation/disruption for the group of companies that remained active for the whole observation period. However, since our sample consists of sub-investment grade firms, many of whom defaulted or filed for Chapter 11 protection during the timeframe considered, we cannot avoid considering the value disruption caused by this set of companies. It is not easy to estimate the loss for shareholders in this circumstance, so we rely on estimation. In particular, to estimate the loss given default (LGD) for shareholders we use the methodology developed by Oricchio (2012) and described in paragraph 2.4.3.

First, we start from the default probability of the single company assigned by the rating agencies to the firm's senior debt. As we mentioned in paragraph 2.4.3.1, the default probability is an estimation of the probability that debt holders incur a loss, thus meaning that equity holders have already lost all their capital, since equity is subordinated to debt. To account for the possibility that shareholders incur a loss lower than the 100 per cent of their investment, we implement the methodology presented in paragraph 2.4.3.1 for the estimation of the equity loss given default. If we resume the analogy described in paragraph 2.4.3.2 and we treat the liability side of the balance sheet as it were structured debt, we can identify equity as a junior tranche (subordinated debt) and financial debts (borrowings from the bank) as senior tranches. Thus, we can approximate the equity loss given default to the average corporate debt LGD rates measured by trading prices of junior subordinated bonds estimated by Moody's.[14]

$$\text{Equity LGD} = \text{PD} * 100\% + (1\text{-PD}) * \text{junior subordinated bonds LGD}$$

Indeed, the equity LGD will be pondered for both the possibility that shareholders lose 100% of their investment and for the possibility that they benefit from a positive recovery rate. This methodology allows us to estimate a proxy of the average loss given default that shareholders of the firms which ceased to exist during the observation period may have suffered.

[14] The average corporate debt recovery rate measured by trading prices of junior subordinated bonds by Moody's is 22% for the period 1983-2020. Thus, the LGD would be 100%-22%= 78%.

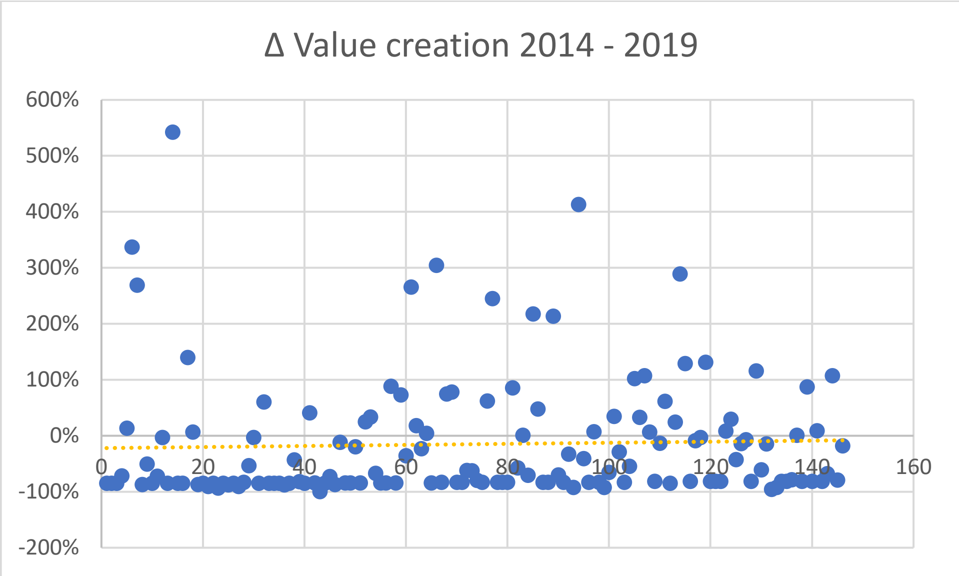

Figure 3.1 - Delta value increase/decrease from 2014 to 2019.

Figure 3.1 shows the distribution of value creation/disruption in the sample of sub-investment grade companies selected (146 firms). As we can see the average results in a negative value (value deterioration) of -0,15065 (table 3.5).

Descriptive statistics	
Mean	-0,15065
Standard Error	0,09087
Median	-0,70144
Mode	-0,84937
Standard Deviation	1,09797
Sample Variance	1,20555
Count	**146**

Table 3.5 - Descriptive statistics of the data sample.

3.6 Regression model

Firstly, we use a multivariate regression model to put all the variables identified to the test and assess whether they can be considered value creation drivers or not.

We are testing the model under two alternative hypotheses:

H_0: The estimated effect that the financial indicator has on the market capitalization is statistically indistinguishable from zero.

H_1: The estimated effect that the financial indicator has on the market capitalization is statistically significant.

As a null hypothesis for the test on the effect of the value creation, the following is set as the 13-factor model:
Model (1):

$$y_i = \alpha_i + \beta_1 \, Size_i + \beta_2 \, MS_i + \beta_3 \, MB_i + \beta_4 \, ROI_i + \beta_5 \, \mathrm{OROIC}_i + \beta_6 ICR_i + \beta_7 \, D.EBITDA_i + \beta_8 \, ROA_i + \beta_9 \, OCF_i + \beta_{10} \, PD_{1\,i} + \beta_{11} \, PD_{6\,i} + \beta_{12} \, UP.DOWN_i + \beta_{13} \, Z_i + \varepsilon_i \text{ for } i = 1, 2, \ldots, 146$$

The financial indicators that we used as variables for the multivariate regression model are reported in Appendix A.
The firm size effect is captured by the variables *Size* and *MB*. Previous research shows dichotomous results when it comes to the company size, some papers identified size as a variable positively correlated with higher turnaround success, thus able to separate non-turnaround companies and turnaround companies, although not able to impact the level of turnaround's performance (Hansen, 2012). However, Bruton *et al*. (2003) results show that, in the case of East Asian companies, the size determinant is negatively associated with turnaround performance.
The expected result of the Operating Cash Flow determinant (*OCF*) is positive, as Karas *et al.* (2020) spotted a negative correlation coefficient when assessing *OCF*'s ability to predict financial distress. Similarly, we would expect a negative correlation between both PD_1 and PD_6 and the value creation since a higher PD implies higher distress and a higher probability of default. The *UP.DOWN* variable, which tells us if the company has undertaken a turnaround during the observation period, is expected to be positively correlated with the value creation.

The dependent variable y is the value creation measure, that we identified as the firm's increase in market capitalization. To account for both the possibilities that the company creates value and that it destroys value we implemented a probit model. A probit model is a statistical regression wherein the dependent variable can assume only two outputs (0 or 1). The objective of the probit approach is to evaluate the probability that an observation will fall into one of the two predetermined categories. In this context, it is possible to use the probit to estimate the probability that the company either creates or destroys value in the time frame 2014-2019. Indeed, the indicator variable will be a Dummy assuming the value of 1 if the company creates value or 0 if the company destroys value.

$$\text{Value creation Dummy (y)} \begin{cases} 1 \rightarrow \text{the company creates value} \\ 0 \rightarrow \text{the company destroys value} \end{cases}$$

The value creation for shareholders is indicative of an increase in the company's market capitalization. However, the category of value destruction (0) contains companies whose market capitalization decreased in the observation period, but also firms that filed for Chapter 11 protection, were acquired, or were delisted, for whom Bloomberg data are no more available.

The independent variables chosen as inputs in the Model (1) can be grouped into four classes: accounting measures that can be extracted from the firms' balance sheets such as ROA, Net Debt/EBITDA, and CFFO, financial indicators that use market values such as Market capitalization, P/Sales, and P/Book, credit rating indicators provided by rating agencies such as the default probability and Upgrading/Downgrading, and finally measures that have a demonstrated ability in the prediction of the default probability such as the Altman Z-score.

The results of the regression Model (1), thus the variables that are statistically significant (rejection of the null hypothesis), are then used as inputs for an optimized multivariate regression.

Model (2):

$$y_i = \alpha_i + \beta_1 Size_i + \beta_2 MS_i + \beta_3 ICR_i + \beta_4 ROA_i + \beta_5 OCF_i + \beta_6 UP.DOWN_i + \varepsilon_i \text{ for } i = 1, 2, \dots, 146$$

Finally, we perform some sets of univariate regressions to be sure that no statistically significant linkages that could potentially influence the value creation were missed in the previous analysis.

Model (3): $y_i = \alpha_i + \beta_1 \, ICR\,i$ for i =1, 2,…., 146

Model (4): $y_i = \alpha_i + \beta_1 \, D.EBITDA_i$ for i =1, 2,…., 146

Model (5): $y_i = \alpha_i + \beta_1 \, Z_i$ for i =1, 2,…., 146

Following the same approach of the inherent previous literature, the coefficients presented in the next section are estimated using Ordinary Least Squares (OLS). After computing the coefficients, a two-tailed significance test is realized for the individual variables to assess their statistical significance (the statistical significance of each coefficient is estimated through a T-test). For each model, a standard F-test for overall significance is also performed.

3.7 Results

This section provides an analysis of the potential drivers of shareholders' value creation, intending to assess whether the variables identified at time 0 (2014) can be considered good predictors of value creation at time 6 (2019).

Model (2):

	(2)
α	0,30136***
	(0,03349)
Size	-0,16416***
	(0,04856)
ROA	-0,07895**
	(0,03437)
CFFO	0,11999***
	(0,04406)
UP.DOWN	0,22541***
	(0,03701)
N	**146**
R Square	**0,25936**
Adjusted R Square	**0,22739**

*Standard errors in parentheses; The superscripts ** and *** denote significance at the 5% and 1% level, respectively.*

Table 5.1 - Results of the regression analysis for the model (2).

Source: Personal elaboration

For each model, Appendix B reports the coefficients of the variables and the corresponding standard errors (in parentheses). The sample size, which is 146 for all the regressions, the R square, and the adjusted R square of the regressions are also indicated.

Firstly, we are going to explain the results coming from the model (3), (4), and (5) because they are in some ways the most unexpected. In models (3), (4), and (5) we employed a set of univariate regressions to test if the variables Net Debt/EBITDA (*D.EBITDA*), *ICR*, and Altman's Z-score (*Z*) are statistically significant in explaining the increase in market capitalization. As it was pre-empted in paragraph 3.2, we expected a strong negative correlation between these variables and the value creation since they are the most widely utilized by scholars in the models that forecast the default and bankruptcy probability. However, there are no signs of a statistically significant relationship between *D.EBITDA*, *ICR*, or *Z* and the increase in market capitalization (Appendix B). The conclusion that we can draw from this result is that the variables that are statistically significant in the prediction of default are useless when trying to predict the potential value creation of highly distressed companies. In this regard, we are not debating the usefulness of such measurements to assess the default probability, which is their primary objective, however, we are merely observing their lack of statistical significance when trying to adapt their scope in forecasting value creation.

Moreover, starting from the empirical failure of models (3), (4), and (5), we present model (2), which is a 6-variables regression. The dependent variable (y) is the value creation that we aim to explicate, and it is a dummy variable that assumes the value 1 if there is value creation (increase in the market capitalization) and 0 otherwise. The resulting F-test of this regression is 8.11, with a significance level of 1.59E-07, which can be considered fairly satisfactory. From the results of model (2) summarized in Table 5.1, it emerges that the statistically significant indicators of value creation are the coefficients of the variables *Size, ROA, CFFO,* and *UP.DOWN*.

Model (2) shows how the coefficient *Size*, which identifies the firm's market capitalization at t=0, is negatively correlated to the value creation and statistically significant at a 1% significance level. This result is consistent with Bruton *et al*. (2003), that detected a negative relationship between the size determinant and turnaround performance. The negative correlation between the company's size and the value creation in turnarounds can be explained by the fact that smaller firms incorporate higher growth potential therefore the equity markets' expectations on the outcome of a turnaround are better. Indeed, the larger the company's size the greater the organizational complexity and the number of parties involved, which can limit the turnaround potential and the chances of a positive value creation, due to the difficulty to balance the interests of employees (trade unions), governments, creditors, etc. with the needs of the company to restructure. Nevertheless, we are not denying the fact that companies with a larger size have a lower probability to incur default, liquidation, and dissolution.

The ROA indicator appears to be highly significant in model (2) at 5% significance level. However, the Return on Assets is negatively correlated with the increase in market capitalization at t=6. A plausible explanation for this quite counterintuitive relationship can be found in the lending process. Needless to say, to implement a successful turnaround process and create value for shareholders the firm needs to invest and have access to new funding. When deciding whether to grant funds to distressed companies, banks and financial intermediaries usually adopt an asset-based lending process (higher total assets result in a lower ROA). Indeed, the companies that have a higher amount of total assets which can provide strong collateral, thus granting the banks' support to the turnaround process, have higher probabilities to create value.

Further, model (2) illustrates how the coefficient *Cash Flows From Operations* is positively correlated with the increase in market capitalization and statistically significant at 1% significance level. This result can be interpreted intuitively by the fact that the higher the firm's cash flows streaming from operations, the higher the chances that it will create value in the future. As we described in paragraph 2.2, if the company has a good level of CFFO, this means that the core business is intact and the issues may be of financial nature, such as a debt overhang, in which instance a debt restructuring may be the solution to restore the company's going concern.

The *turnaround hypothesis* is confirmed by model (2) at a 1% significance level. This is in line with our expectations that when a firm can undertake a successful turnaround process this has positive implications for the equity holders' value creation. A potential limitation of the UP.DOWN indicator is that it is observed *ex-post*. It is quite problematic to forecast at t=0 if a company will undertake a turnaround process. For the purpose of this study, it was necessary to use an indicator observed *ex-post* in order to have a sound and reliable measurement. Nevertheless, a good proxy of this variable is credit rating outlooks, which can be read as reasonable upgrading/downgrading probability assessed based on the company's peculiar situation.

Conclusions

This last section is meant to provide a final summary of the outcomes of the analysis and their implications, as well as to answer the question “Are junk companies a good deal?”, which was the focal point of the empirical analysis and the ultimate goal of this thesis.

The sub-investment grade credit market is becoming increasingly relevant. According to S&P estimations, the high-yield-rated debt market grew by 4 per cent from 2018 to 2019 in the US and amounted to $2.6 trillion as of January 1st, 2019 (pre-crisis levels). Indeed, speculative-grade debt accounts for a total of 28 per cent of the American corporate debt market, making sub-investment grade firms a burning topic.

Notwithstanding the rising interest among practitioners, the value creation potential of sub-investment grade firms is still under debate, and up to date, there is a lack of empirical evidence.

The present empirical analysis examines 13 factors that could be potential value drivers, identified from previous research on bankruptcy, turnaround, and default probability. The examination considers a sample of 146 troubled companies, publicly traded in the European and American capital markets in the period between 2014 and 2019. The focus is to identify the troubled companies that are more promising for investors, based on their intrinsic probability of surviving the crisis and undertaking a successful turnaround.

The results of the multivariate regressions performed on the 146 companies of the data sample offer some valuable insights. Indeed, we can notice that for sub-investment firms which are strongly distressed at t=0, the probability to have a positive value creation at t=6 depends on the firm’s *Size* (market capitalization), *ROA*, and *CFFO* at t=0, as well as on the expectation of turnaround. In particular, the results of the empirical analysis show that the *Size* has a negative impact on value creation, meaning that smaller companies have higher possibilities to increase their market capitalization and to benefit from a successful turnaround since firms with a smaller *Size* incorporate higher growth potential, therefore the equity markets’ expectations on the outcome of a turnaround are better. The *ROA* indicator has a negative correlation with the value creation as well, signaling the importance of having a strong asset base, even at the expense of the operating income. Moreover, the *CFFO* variable has a positive effect on the firm’s capacity to increase the market capitalization, since if the company has a good level of cash flows streaming from operations, it is easier to implement the turnaround process and create value for shareholders.

The *turnaround hypothesis* that we included in the model is strongly correlated with the value creation for shareholders, showing that if we consider a reasonable probability of turnaround based on the company's peculiar situation, we are able to predict the increase in the market capitalization.

Moreover, to answer the question "Are junk companies a good deal?" we started by performing a descriptive statistic on the data sample. From this first assessment, it emerged a negative average value creation for the period 2014-2019 of -15,06 per cent, which is not surprising given the fact that we are analyzing companies considered "junk". Nevertheless, we built a model to identify the statistically significant indicators that can offer a guide when trying to forecast (at t=0) which companies have a higher probability to create value at t=6. Thanks to the analysis performed (Model (2)), we have been able to identify four variables that are statistically significant in explaining the value creation for equity holders, namely: *Size, ROA, CFFO,* and *UP.DOWN*.
We can conclude that if we invest in all junk companies without discrimination, we will probably incur a loss (value disruption). However, if we select our portfolio of securities considering the results of Model (2) we have a higher probability of achieving a positive value creation.

Lastly, it is necessary to mention that the results presented do not claim to be exhaustive, since they are based on data and information publicly available at the time of the model estimations and do not account for other important variables which can be difficult to assess, such as the features of the turnaround process, the quality of the management team, and the effectiveness of debt restructuring. Nevertheless, bearing in mind the aforementioned limitations, this thesis can provide the starting point to future research and food for thoughts to distressed assets and rescue investing practitioners.

Bibliography

Altman. E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance*, 23, No. 4, September, 589-609.

Altman, E. I. (2020). Covid-19 and the credit cycle. *Journal of Credit Risk*, *16*(2), 1–28. https://doi.org/10.21314/JCR.2020.262

Altman, E. I., Hotchkiss, E., & Wang, W. (2019). *Corporate Financial Distress, Restructuring, and Bankruptcy*, 165-173. https://doi.org/10.1002/9781119541929

Angeloni, I. (2020). *Non-Performing Loans : An Old Problem in a new situation*. *December*, 107–118.

Banca d'Italia. (2021). *CXXVII Relazione annuale*. https://www.bancaditalia.it/pubblicazioni/relazione-annuale/2020/rel_2020.pdf

Bruton, G. D., Ahlstrom, D., & Wan, J. C. C. (2003). Turnaround in East Asian firms: Evidence from ethnic Overseas Chinese communities. *Strategic Management Journal*, *24*(6), 519–540. https://doi.org/10.1002/smj.312

Buttignon, F. (2015). Distressed Firm Valuation: Reorganization Plan and Going-Concern Capital Value. *SSRN Electronic Journal*, *July*. https://doi.org/10.2139/ssrn.2567651

Cerra, V., Fatas, A., & Saxena, S. (2020). Hysteresis and Business Cycles. *IMF Working Papers* (Vol. 20, Issue 73). https://doi.org/10.5089/9781513536996.001

Chappatta, B. (2021). Distressed-Debt Hedge Funds Have Nowhere to Go. *Bloomberg*. https://www.bloomberg.com/opinion/articles/2021-02-04/distressed-debt-hedge-funds-have-nowhere-to-go

Damodaran, A. (2010). The Dark Side of Valuation. *Financial Times-Prentice Hall*. Pearson Education, Second edition.

Dang, C., (Frank) Li, Z., & Yang, C. (2018). Measuring firm size in empirical corporate finance. *Journal of Banking and Finance*, *86*, 159–176. https://doi.org/10.1016/j.jbankfin.2017.09.006

Dun & Bradstreet Worldwide Network. (2019). *Global Bankruptcy Report 2019*. 1–19. https://dnb.ru/media/entry/56/217433_Global_Bankruptcy_Report_2017_9-20-17.pdf

Hallak, I., Harasztosi, P., & Schich, S. (2018). Fear the Walking Dead? Incidence and Effects of Zombie Firms in Europe. https://doi.org/10.2760/314636

Hansen, A. V. (2012). *Corporate Turnaround and Corporate Governance*. http://studenttheses.cbs.dk/bitstream/handle/10417/3662/anders_vest_hansen.pdf?sequence=1

IMF. (2021). World Economic Outlook Update. *Internation Monetary Fund* (Issue July 2021). https://www.imf.org/en/Publications/WEO/Issues/2021/07/27/world-economic-outlook-update-july-2021

Karas, M., & Reznakova, M. (2020). Cash flows indicators in the prediction of financial distress. *Engineering Economics*, *31*(5), 525–535. https://doi.org/10.5755/j01.ee.31.5.25202

Kisgen, D. J. (2006). Credit ratings and capital structure. *Journal of Finance*, *61*(3), 1035–1072. https://doi.org/10.1111/j.1540-6261.2006.00866.x

McGowan, M., A., Andrews, D., Millot, V. (2018). The walking dead? Zombie firms and productivity performance in OECD countries. *Economic Policy, Volume 33, Issue 96, October 2018, Pages 685–736. https://doi.org/10.1093/epolic/eiy012*

Mckiernan, P. (2009). Turnarounds. *Oxford Handbooks Online*, 1–54. https://doi.org/10.1093/oxfordhb/9780199275212.003.0026

Moscatelli, M., Narizzano, S., Parlapiano, F., & Viggian, G. (2019). Corporate default forecasting with machine learning. *Temi di discussione (Working Papers), Banca d'Italia.*

Muggenthaler, P., Schroth, J., & Sun, Y. (2021). The heterogeneous economic impact of the pandemic across euro area countries. *Economic Bulletin 5/2021, European central bank.*

https://www.ecb.europa.eu/pub/economicbulletin/focus/2021/html/ecb.ebbox202105_03~267ada0d38.en.html

Oricchio, G. (2012). Private Company Valuation How Credit Risk Reshaped Equity Markets and Corporate Finance Valuation Tools. *Palgrave Macmillian* (Vol. 1).

Platt, E. (2021). Distressed debt specialist Howard Marks warns on corporate borrowing burden. *Financial Times*. https://www.ft.com/content/5585b123-7b9d-40fe-8f63-95f7491e8193

Reedy, V. (2012). Intrinsic Value Estimation Through Fundamental Analysis – A Case Study of Dr. Reddy's Laboratories Ltd., Hyderabad. *SSRN Electronic Journal*, *March 2012*. https://doi.org/10.2139/ssrn.3477886

Senbet, L. W., & Wang, T. Y. (2012). Corporate financial distress and bankruptcy: A survey. *Foundations and Trends in Finance*, *5*(4), 243–335. https://doi.org/10.1561/0500000009

Serrano-Cinca, C., & Gutiérrez-Nieto, B. (2013). Partial least square discriminant analysis for bankruptcy prediction. *Decision Support Systems*, *54*(3), 1245–1255. https://doi.org/10.1016/j.dss.2012.11.015

Shabib-ul-hasan, S., Farooq, S., & Muddassir, M. (2015). Stock Returns Indicators : Debt to Equity, Book to Market , Firm Size and Sales to Price. *Journal of Poverty, Investment and Development*, *16*(1981), 25–32.

Singal, M. (2013). Firm Credit Rating as a Measure of Organizational and Financial Performance. *Journal of Business & Financial Affairs*, *02*(03). https://doi.org/10.4172/2167-0234.1000e135

Singh, P. K., & Anand, R. (2013). Shareholders ' Value Creation and Market Capitalization - A Case Study of Automobile Industry in India. *Journal of Contemporary Research in Management*, *8*(3), 1–12.

Slatter, S., Lovett, D. (1999). Corporate recovery: Managing companies in distress. Penguin, London.

Sylvester, J. (2020). Why Hedge Funds Invest in Distressed Debts. *Otranation*.

https://www.otranation.com/why-hedge-funds-invest-in-distressed-debts/

Vulpiani, M. (2014). Special Cases of Business Valuation. McGraw-Hill, First Edition.

Wigglesworth, R. (2021). Distressed debt funds sparkle in Covid recovery. *Financial Times, August 2021*. https://www.ft.com/content/74c50d58-d46e-4c1f-b806-3725ec7581fb

Wojewodzki, M., Poon, W. P. H., & Shen, J. (2018). The role of credit ratings on capital structure and its speed of adjustment: an international study. *European Journal of Finance*, *24*(9), 735–760. https://doi.org/10.1080/1351847X.2017.1354900

Zanda, G., Lacchini, M., Onesti, T. (2013). La valutazione delle aziende. Giappichelli, Sixth edition.

Weblinks

ECB:https://www.ecb.europa.eu/pub/economicbulletin/focus/2021/html/ecb.ebbox202105_03~267ada0d38.en.html

NYU: http://people.stern.nyu.edu/adamodar/New_Home_Page/TenQs/TenQsBottomupBetas.htm

Olstein: Finding Value in Corporate Turnarounds - Olstein Funds

PWC: https://www.pwc.com/us/en/services/deals/library/bankruptcy-outlook.html

S&P:https://www.spglobal.com/ratings/en/research/articles/210526-default-transition-and-recovery-the-u-s-speculative-grade-corporate-default-rate-could-fall-to-4-by-march-11972018
https://www.spglobal.com/en/research-insights/articles/u-s-corporate-debt-market-the-state-of-play-in-2019

Appendix

Appendix A – Variables description

This appendix provides a detailed definition of all the variables included in the models

Size: The company's market capitalization at t=0

MS: The ratio of capitalization to sales value

MB: The ratio of capitalization to book value

ROI: Return on investments

OROIC: Operating income to total invested capital

ICR: Interest coverage ratio

D.EBITDA: Net debt on EBITDA

ROA: Return on assets

OCF: Operating cash flows

PD_1: Default probability after 1 year

PD_6: Default probability after 6 years

UP.DOWN: Upgrading/downgrading in the credit rating

Z: Altman's Z-Score

Appendix B – Regression Models

	(1)	(2)	(3)	(4)	(5)
α	0,30136***	0,30136***	0,30136***	0,30136***	0,30136***
	(0,03261)	(0,03349)	(0,03811)	(0,03818)	(0,03820)
Size	-0,15036***	-0,16416***			
	(0,04923)	(0,04856)			
MS	0,06574*	0,06327			
	(0,0403)	(0,03654)			
MB	-0,05304				
	(0,03843)				
ROI	-0,00469				
	(0,06355)				
OROIC	0,09235				
	(0,08898)				
ICR	-0,05727	-0,00013		-0,02383	
	(0,04053)	(0,03553)		(0,03761)	
D.EBITDA	-0,0457		-0,03452		
	(0,03341)		(0,03551)		
ROA	-0,1252***	-0,07895**			
	(0,04355)	(0,03437)			
CFFO	0,08449*	0,11999***			
	(0,04488)	(0,04406)			
PD1	0,02605				
	(0,06609)				
PD6	-0,09989				
	(0,06901)				
UP.DOWN	0,22115***	0,22541***			
	(0,03694)	(0,03701)			
Z	-0,0434				-0,01791
	(0,04443)				(0,03774)
N	**146**	**146**	**146**	**146**	**146**
R Square	**0,33305**	**0,25936**	**0,00651**	**0,00278**	**0,00156**
Adjusted R Square	**0,25979**	**0,22739**	**-0,00038**	**-0,00414**	**-0,00537**

Appendix B - Results of the regression analysis for the models (1), (2), (3), (4), and (5).

Source: Personal elaboration

Summary

In 2020 the global macro-economic scenario has been overturned by the health emergency caused by the Covid-19 pandemic. At the beginning of last year, economic conditions changed dramatically, reflecting a worldwide downturn in economic activity unprecedented in modern history. According to IMF estimates, global GDP in 2020 fell by 3.3 per cent, representing the sharpest contraction since World War II. The recession negatively affected the international trade, which fell by 8.9 per cent, strongly driven down by the services contractions due to restrictions on the mobility of goods and people.

The economic effects of the Covid-19 crisis have varied across sectors and geographic areas, reflecting the severity of the health pandemic at the local level and the responses of governments' policies. Monetary policies have prevented the pandemic crisis from turning into a financial crisis by ensuring liquidity in the markets and facilitating borrowing through various initiatives, including bond purchase plans. Tax policies have played a crucial role in supporting household and corporate incomes, especially in developed countries, and preventing a widening of the recession.

In 2020 Chapter 11 filings soared, increasing by about 29 per cent, going from 6.011 filings in 2019 to 7.743 in 2020, according to the Bloomberg BANBT11 index, which accounts for all new US bankruptcy filings concerning the business category. However, the rise in bankruptcy activity can be considered modest if we compare it to the disruption that companies were forced to tackle in 2020, thanks to government aids and availability of liquidity, which led to fewer corporate restructurings than expected by economists. Further, it's been proven that the Covid-19 crisis has been the catalyst to further the restructuring of companies that had already shown signs of trouble before the pandemic. According to a PWC estimation, approximately nine of the ten largest companies that decided to file for Chapter 11 were already on distressed watchlists at the beginning of 2020, as a demonstration that the pandemic impact was not the primary cause of distress for these businesses.
Moreover, the industries most hit by the restructurings wave are retail, energy, travel, and hospitality, which suffered a huge decrease in demand due to restrictive measures.

Bankruptcy is the last stage of the corporate crisis. However, credit rating agencies employ a broad definition of crisis, using the concept of default. Financial default occurs when a borrower fails to repay a debt, including interest or principal and assumes the status of non-performing. This definition of default allows rating agencies to classify as defaulted not only companies that incurred in

bankruptcy, but also firms that missed or delayed the repayment of a contractually obligated interest or principal. Indeed, credit rating is designed to assess the quality of bond issued, measured in terms of the issuer's estimated solvency and its likelihood of default. Credit ratings are extremely useful since they can be considered as a proxy for companies' default probability, thus facilitating investors to assess the value of financial instruments and determine their appropriate required yield consistent with their default risk (Wojewodzki et al., 2018). The rating scales are generally split into two groups, between the safer investment-grade securities (from Aaa to Baa3/AAA to BBB–) and the riskier high-yield bonds (below Baa3/ BBB–). These historical data on default rates collected by rating agencies are relevant not only to investigate the historical performance but also to predict forthcoming default rates.

As estimated by Altman et al. (2019), in 2018 high yield securities amounted to $1,656 billion, accounting for 22 per cent of the North American corporate bond market, which itself has been steadily increasing from the late '90 until nowadays.
Indeed, default and default loss expectations are the most crucial variables for investors that trade high yield and high-risk corporate bonds (Altman et al., 2019).
Rating agencies explain that during the global crisis triggered by Covid-19 defaults increased, but to an inferior extent than recent recessions (for instance compared to the Great Financial Recession of 2008-2009). Corporate downgrades also increased, to near a record high. However, in both instances, corporate defaults and downgrades were mainly restricted to the riskier rating classes, resulting overall in good rating performance in 2020.

The sub-investment grade credit market is becoming increasingly relevant. According to S&P estimations, the high-yield-rated debt market grew by 4 per cent from 2018 to 2019 in the US and amounted to $2.6 trillion as of January 1st, 2019 (pre-crisis levels). Indeed, speculative-grade debt accounts for a total of 28 per cent of the American corporate debt market, making sub-investment grade firms a burning topic.

Notwithstanding the rising interest among practitioners, the value creation potential of sub-investment grade firms is still under debate, and up to date, there is a lack of empirical evidence.
For this reason, the focus of this dissertation is on distressed companies, defined as companies that struggle to reimburse interest payments and to fulfill other contractual commitments, as well as company's whose debt and equity values reflect the potential or likelihood of default or liquidation scenarios (Damodaran, 2010 and Vulpiani, 2014).

Firstly, we describe the methodologies useful to evaluate companies with a medium to high risk of insolvency (sub-investment grade credit rating). In particular, obligations rated below the B class are considered speculative and are subject to high credit risk. The companies that fall within this category are likely to have sufficient asset quality, although fleeting liquidity crunch, high leverage, oftentimes managerial shortcomings in the product positioning, and poor market penetration.
The financial and/or operational disequilibrium that triggers the company's crisis is an out-of-ordinary event, which has significant implications on valuation methods, because of the uncertainty in the estimation of future cash flows, the higher difficulty in the estimation of the riskiness, and the impossibility to take advantage of historical performance data because they are indicative only if standard efficiency levels hold.

Indeed, the cost of equity conventionally used by valuation methods does not reflect the proper credit risk of subjects, since it resorts to the leverage ratio (Debt/Equity) as a proxy of credit riskiness (Capital Asset Pricing Model), without considering the default probability. This approximation works perfectly in the case of investment-grade companies, which have a negligible default probability (see Table 1.1). On the other hand, when evaluating high-yield companies, which can have a default probability as high as 75.29 per cent (10 years average cumulative default rate for Ca-C- rated companies), neglecting to account for credit risk becomes unbearable. In this context the probability of default is crucial since the debt repayment ability depends on the firms' cash flow generation, which can be insufficient and/or unstable for high yield companies, triggering high credit risk levels.

Nevertheless, the correct identification and estimation of the credit risk should precede the firm's economic capital evaluation process, to firstly assess the long-term insolvency probability and define the firm's status and choose the most appropriate valuation method (Zanda *et al*., 2013).

Indeed, evaluating the causes of decline can be useful to estimate the crisis' degree of recoverability. From this standpoint, the fundamental analysis should be the square one to examine the crisis' grounds. Generally speaking, the causes of distress can be occasional or structural, while in the first matter there are good chances of restructuring and implementing a turnaround process to emerge from the tough situation, when the issues have a structural nature, exit the crisis phase can be extremely more challenging.
The fundamental analysis' objective is to determine and appraise the causes, such as the global context and the specific factors, that led to a situation of financial distress. In particular, it is important

to perform carefully the analysis of the factors that negatively influence the performance (industry-related, organizational specific, and/or managerial), the assessment of the severity of losses, and the review of the historical trend and structure of the company's losses. At its broadest definition, the fundamental analysis is a stock valuation method that checks both financial and economic analysis to forecast stock prices movements (Reedy, 2012). The process of fundamental analysis involves examining the firms' fundamental financial position through key ratios to assess its financial health with the aim to estimate the stock value and how the stock is valued by the market (undervalued/overvalued). Indeed, the fundamental data examined in the process span from financial indicators to non-financial data such as estimations of demand growth, industry trends, changes in the target market, and potential changes in public policies. The first step to estimate the intrinsic value is to assess the current and future status of the global economy. After that, it is possible to proceed with the analysis of the specific company. In particular, the factors to investigate further are the core competencies and fundamental strengths which can generate a competitive advantage for the firm, such as management skills, performance history, development potential, low production costs, brand allure, etc.

The topic of this dissertation gravitates around "junk companies", defined as firms with a medium to high risk of insolvency, thus ranked in the sub-investment grade rating category.
Indeed, the techniques to perform a correct valuation of high-yield companies are quite different from standard valuation methods, nevertheless, it is crucial to master them properly, since the inaccurate assessment of a troubled business can cause the investor to stumble into value traps.
In particular, equity prices of sub-investment grade companies are hugely influenced by the security's credit risk. Indeed, whereas the cost of capital of investment grade firms depends on the market risk, the cost of the capital of sub-investment grade firms depends mainly on the risk of default (Ermotti S. introduction to Oricchio (2012)). This dichotomy should be meticulously considered when assessing the equity risk premium in order to account for the default probability in the valuation process.

For the purpose of this thesis, the equity risk premium is estimated according to the methodology developed by Oricchio (2012) and Zanda *et al.* (2013) based on the following steps:

1. Estimation of shareholders' expected loss (default probability (PD) and loss given default)
2. Determination of risk-adjusted spread through the junior subordinated pricing model
3. Integration of CAPM and Fixed Income Approach for the estimation of risk premium (IPM)

The Fixed Income Approach (FIA) just mentioned estimates the equity risk premium based on shareholders' loss given default, by using the junior subordinated notes pricing model. This approach is particularly convenient because it allows accounting for the credit risk estimated by the rating agencies for each credit rating class when estimating the risk premium.

$$(1+\text{ i BTP}) = \text{PD equity} * \text{loss given default equity} + (1 - \text{survival probability}) * (1 + \text{i BTP} + \text{i}_2)$$

$$\text{i}_2 = \frac{\left((\text{PD equity} * \text{LGD equity}) + \text{survival probability}(1 + i \text{ BTP})\right)}{(1 - \text{survival probability})}$$

The resulting risk-adjusted spread is the risk premium of equity, which accounts not only for the probability of default but also for the probability of survival.

The subjects that more than everyone master distressed valuation methods are hedge funds. Indeed, hedge funds managers that pursue a value-oriented strategy seeking to capitalize on the risk mis-pricings in sub-investment grade credit markets need to master these techniques perfectly to spot the mentioned mis-pricings. Distressed debt funds are wizards in picking up the bonds of stricken companies that have the highest possibility to thrive.

Especially this year, hedge funds seeking to profit from troubled companies enjoyed the greatest returns since the Great Financial Crisis, thanks to the stimulus-driven market rally which raised the price of debt about to default, reaching returns as high as 11.45 in the period January-July 2021 (Wigglesworth, 2021). This marks the best performance in 2021 for all major hedge funds, compared to the other investment strategies, according to Eurekahedge. The outperformance enjoyed in 2020 and 2021 by funds that invest in the hardest-hit firms and segments of the economy stems from the positive signals of economic recovery after the pandemic, which has been boosted by central banks' aids and by efforts in the vaccination campaign.

The objective of this thesis is to identify the drivers of value creation that can be spotted when highly distressed companies undertake a turnaround process and manage to avoid Chapter 11. For this scope, distressed companies are the starting point of this research. The focus is to identify which troubled companies to bet on, based on their intrinsic probability of surviving and becoming profitable again. The process undertaken to analyze the value creation of sub-investment grade companies is the following:

1. Identification of the data sample

2. Identification of the financial indicators that will be statistically tested as potential drivers of the value creation and first multivariate regression
3. Application of basic descriptive statistics tolls for a first screening of the sample
4. Re-definition of the sample as the probability that a sub-investment grade firm (highly distressed) creates value for shareholders
5. Multivariate regression in two stages to evaluate the variables that significantly influence the value creation and test their predictive ability
6. Univariate regression of the indicators commonly used to assess the default probability (Net debt/EBITDA, ICR, Altman's score), to test if they are significant to estimate the value creation of distressed companies

The study considers a sample of 146 troubled companies, publicly traded in the European and American capital markets. The observed period spans from 2014 to 2019 and includes all firms with non-missing values for the measures chosen to estimate the value creation. The general population of companies has been identified through Bloomberg and Refinitiv databases.

The starting point to identify the companies in a situation of stress and distress has been the high yield credit rating market, considering sub-investment grade companies a proxy of all businesses struggling to meet their financial obligations. Indeed, the general population of this analysis includes the securities in the range from B1 to C of Moody's rating scale. Most of the companies in the sample are from North America since the majority of rated issuers are domiciled there.
The industries selected and included in this quantitative analysis are communications, consumer discretionary, consumer staples, energy, real estate, health care, industrials, material, technology, and utilities. On the contrary, financial services (such as banks, asset management funds, insurances, etc.) and governments issuers, which are of no interest for the present research, have been excluded from the preliminary sample.

The variables that have been tested (multivariate regression) as potential value drivers for shareholders of sub-investment grade companies are a set of indicators that have resulted relevant in previous studies on bankruptcy, turnaround, and default probability. The firm size effect is measured as the market capitalization (*Size*) since this measure allows to capture the firm's growth opportunities and also equity market conditions (Dang *et al.*, 2018). The variables *MS* (Price/Sales) and *MB* (Price/Book value) have been included cause they are considered good indicators for stock returns (Shabib-ul-hasan et al., 2015). Thus, we have selected a set of accounting-based indicators for the analysis, namely the *ROI, OROIC,* and *ROA* (Serrano-Cinca et al. 2013). We then included a Cash Flow indicator (*OCF*), with a view to the work of Karas *et al.* (2020), who points out that operating cash flow ratios play a prominent role in financial distress. The Net Debt/EBITDA (*D.EBITDA*) is an indicator widely used by practitioners since it estimates the company's ability to meet its financial obligations. The variables PD after one year and after six years have been included due to the fact that they are considered an objective measure to assess how likely is the company to incur default. Finally, we used the Altman's Z score as a variable (*Z*) since the Altman (1968) model is one of the most commonly used to predict bankruptcy and has been previously employed also for researches on turnaround processes (Mckiernan, 2009).

From a first screening of the sample, we noted that 61.6 per cent of the 146 companies considered are still active at time t=6, in 2019, for a total of 90 firms. Moreover, 22.6 per cent of the companies sampled were acquired in the time frame between 2014 and 2019, 11 per cent of firms filed for Chapter 11 and were delisted contextually, and the remaining 4.8 per cent of businesses were delisted for strategic reasons.
The percentage of companies still active at t=6 is at its maximum for the B1-rated category (the higher rating class considered) and decreases scrolling down to lower rating classes, according to the worsening of the credit rating. Indeed, the incidence of Chapter 11 filings increases going down to the bottom of the column, demonstrating that as the rating observed at t=0 gets worse, the percentage of Chapter 11 cases at t=6 rises.

Further, starting from the 90 companies that remained active during the whole period, 44 (49 per cent) were able to create value for shareholders, registering an increase in the market capitalization.
We then moved forward to analyze not only the average value creation/disruption for the group of companies that remained active for the entire observation period but for the whole sample (active and inactive). To do so we estimated the equity loss given default approximating it to the average corporate debt LGD rates measured by trading prices of junior subordinated bonds estimated by Moody's.

$$\text{Equity LGD} = \text{PD} * 100\% + (1\text{-PD}) * \text{junior subordinated bonds LGD}$$

Thanks to this calculation we obtained the distribution of value creation/disruption in the sample of sub-investment grade companies selected (146 firms) and we noted that the average results in a negative value (value deterioration) of -0,15065.

At this point, we used a multivariate regression model to put all the variables identified to the test and assess whether they can be considered value creation drivers or not, using two alternative hypotheses:
H_0: The estimated effect that the financial indicator has on the market capitalization is statistically indistinguishable from zero.
H_1: The estimated effect that the financial indicator has on the market capitalization is statistically significant.
As a null hypothesis for the test on the effect of the value creation, the following is set as the 13-factor model:
Model (1):

$$y_i = \alpha_i + \beta_1 \, Size_i + \beta_2 \, MS_i + \beta_3 \, MB_i + \beta_4 \, ROI_i + \beta_5 \, \text{OROIC}_i + \beta_6 ICR_i + \beta_7 \, D.EBITDA_i + \beta_8 \, ROA_i + \beta_9 \, OCF_i + \beta_{10} \, PD_{1\,i} + \beta_{11} \, PD_{6\,i} + \beta_{12} \, UP.DOWN_i + \beta_{13} \, Z_i + \varepsilon_i \text{ for } i = 1, 2, \ldots, 146$$

The dependent variable y is the value creation measure, that we identified as the firm's increase in market capitalization. To account for both the possibilities that the company creates value and that it destroys value we implemented a probit model. A probit model is a statistical regression wherein the dependent variable can assume only two outputs (0 or 1). The objective of the probit approach is to evaluate the probability that an observation will fall into one of the two predetermined categories. In this context, it is possible to use the probit to estimate the probability that the company either creates or destroys value in the time frame 2014-2019. Indeed, the indicator variable will be a Dummy assuming the value of 1 if the company creates value or 0 if the company destroys value.

$$\text{Value creation Dummy (y)} \begin{cases} 1 \rightarrow \text{the company creates value} \\ 0 \rightarrow \text{the company destroys value} \end{cases}$$

The results of the regression Model (1), thus the variables that are statistically significant (rejection of the null hypothesis), are then used as inputs for an optimized multivariate regression.
Model (2):

$$y_i = \alpha_i + \beta_1 Size_i + \beta_2 MS_i + \beta_3 ICR_i + \beta_4 ROA_i + \beta_5 OCF_i + \beta_6 UP.DOWN_i + \varepsilon_i \text{ for } i = 1, 2, \ldots, 146$$

Finally, we perform some sets of univariate regressions to be sure that no statistically significant linkages that could potentially influence the value creation were missed in the previous analysis.

Model (3): $y_i = \alpha_i + \beta_1 \, ICR_i$ for $i = 1, 2, \ldots, 146$

Model (4): $y_i = \alpha_i + \beta_1 \, D.EBITDA_i$ for $i = 1, 2, \ldots, 146$

Model (5): $y_i = \alpha_i + \beta_1 \, Z_i$ for $i = 1, 2, \ldots, 146$

Following the same approach of the inherent previous literature, the coefficients presented in the next section are estimated using Ordinary Least Squares (OLS). After computing the coefficients, a two-tailed significance test is realized for the individual variables to assess their statistical significance (the statistical significance of each coefficient is estimated through a T-test). For each model, a standard F-test for overall significance is also performed.

In models (3), (4), and (5) we employed a set of univariate regressions to test if the variables Net Debt/EBITDA (*D.EBITDA*), *ICR*, and Altman's Z-score (*Z*) are statistically significant in explaining the increase in market capitalization. We expected a strong negative correlation between these variables and the value creation since they are the most widely utilized by scholars in the models that forecast the default and bankruptcy probability. However, there are no signs of a statistically significant relationship between *D.EBITDA*, *ICR*, or *Z* and the increase in market capitalization.
The conclusion that we can draw from this result is that the variables that are statistically significant in the prediction of default are useless when trying to predict the potential value creation of highly distressed companies. In this regard, we are not debating the usefulness of such measurements to assess the default probability, which is their primary objective, however, we are merely observing their lack of statistical significance when trying to adapt their scope in forecasting value creation.

Model (2), which is a 6-variables optimized regression, reported the best estimations for the coefficients tested. The dependent variable (y) is the value creation that we aim to explicate, and it is a dummy variable that assumes the value 1 if there is value creation (increase in the market capitalization) and 0 otherwise. The resulting F-test of this regression is 8.11, with a significance level of 1.59E-07, which can be considered fairly satisfactory.
From the results obtained in Model (2), which is the best possible estimation, it emerges that the statistically significant indicators of value creation are the coefficients of the variables *Size, ROA, CFFO*, and *UP.DOWN*.
Indeed, we can notice that for sub-investment firms which are strongly distressed at t=0, the probability to have a positive value creation at t=6 depends on the firm's *Size* (market capitalization), *ROA*, and *CFFO* at t=0, as well as on the expectation of turnaround. In particular, the results of the empirical analysis show that the *Size* has a negative impact on value creation, meaning that smaller companies have higher possibilities to increase their market capitalization and to benefit from a successful turnaround since firms with a smaller *Size* incorporate higher growth potential, therefore the equity markets' expectations on the outcome of a turnaround are better. The *ROA* indicator has a negative correlation with the value creation as well, signaling the importance of having a strong asset base, even at the expense of the operating income. Moreover, the *CFFO* variable has a positive effect

on the firm's capacity to increase the market capitalization, since if the company has a good level of cash flows streaming from operations, it is easier to implement the turnaround process and create value for shareholders. The *turnaround hypothesis* that we included in the model is strongly correlated with the value creation for shareholders, showing that if we consider a reasonable probability of turnaround based on the company's peculiar situation, we are able to predict the increase in the market capitalization.