Market anomaly exploitation using a ternary credit metric model

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Abstract

Companies may trade at low multiples due to undervaluation, financial distress or expected restructuring under chapter 11. Hence, Graham's technique to find undervalued stocks by identifying low PE ratios seems simplistic. In this paper, I present a ternary credit metric model that selects stocks trading at low multiples while controlling for sound credit metrics in a three step process. This provides a cleaner identification strategy of undervalued stocks. Over the period from 1999 to 2011, the ternary model outperforms the S&P500 by 11% annually while its Sharpe ratio is 37% higher than a benchmark solely based on low multiples. The credit metric model avoided 20 bankruptcies which would have been invested in based on the PE ratio alone, and the model yielded significantly higher risk adjusted returns.

Introduction

Academic research provides an array of discovered market anomalies. The price to earnings ratio has been documented numerously before – Basu (1977), Jaffe, Keim and Westernfield (1989) – and also from different angles, e.g. book to market value (Fama, French and Kenneth (1993)). Haugen and Baker (1996) found significant evidence of positive payoffs to measures of current profitability and also discovered cash flow to price anomalies as had Lakonishok et al. (1994). Even though the average appreciation of a "cheap" security relative to a benchmark or relative to an "expensive" security is a remarkably consistent empirical pattern, efficient market fans will conclude, that the security is cheap because it is riskier, and that the risk adjustment is misspecified (Hirshleifer (2001)). According to efficient market theory, the quality of a company should be reflected in its respective market value. Since the price earning (PE) ratio in most cases reflects the market's expectation of the underlying asset's future performance, investment decisions solely based on this particular multiple should not necessarily result in superior risk adjusted returns. Indeed, stocks often trade depressed due to potentially hazardous circumstances that the company faces which may not revert over the expected investment horizon. Such circumstances may include reputational damage, bankruptcy, changes in the legal or regulatory environment or political risks. Particularly shares of companies expected to undergo chapter 11 restructuring are usually trading at very low PE ratios. The obligations of companies in chapter 11 towards their shareholders – then called predecessor shares – are typically canceled, which results in a loss of the entire investment. For deleveraging purposes debt is swapped for equity, which then is called successor common shares. This implies that picking stocks based on low multiples is like fishing in a toxic lake, the fish floating on the surface may seem like an easy catch, but there is something fundamentally wrong with them. The ternary model intends to improve this risk associated with PE investing to convert simple superior returns into risk adjusted superior returns measured by the Sharpe ratio. To avoid picking up a distressed stock at low multiples – e.g. in midst of bankruptcy – the credit metrics model introduces two screening parameters.

Companies with strong cash generation have lower gearing ratios despite their natural capacity to bear more debt, which makes losses through bankruptcy and financial distress less likely as leeway from high margins and low leverage provides a margin of safety in economic turmoil and recession. Accordingly, the ternary model's first step of market screening is based on the ability to generate cash. Before choosing a particular metric though, the purpose thereof must be assessed. Profitability must ultimately reflect the operational cash generation ability of a firm. As such, the FFO margin has some distinct advantages relative to an EBITDA proxy, the net income margin or cash from operations (CFO). While EBITDA does not account for any cash attributed to tax and interest payments, these are reflected in the FFO. Since the goal is to measure the amount of cash generated after having met all obligations to conduct business, interest on capital as well as taxes must be deduct. Net income includes items below the line such as income from affiliates – subsidiaries accounted for by the equity

method – which reflect cash flows that are not physically accessible and therefore provide a distorted proxy of what the business' operations generate in terms of cash. CFO reflects working capital changes distorting the reality of the underlying operation. A business that struggles to generate cash may decrease its inventory or try to cut its days receivables which boosts CFO. This impact stays hidden in the CFO, which then states a larger cash stream than the underlying business is really able to generate. For instance, inventory can be lowered over one period, but not indefinitely, and it will likely revert at some point again. Funds from operations is the purest measure of the amount of cash a given operation yielded over a given time period, and accordingly it is the favored metric used by credit agencies such as Moody's, Standard & Poor's and Fitch. The ternary model computes the FFO margin as follows:

$$FFO\ margin = \frac{\theta_t + (\varepsilon_t - \varepsilon_{t-1} + \gamma_t - \gamma_{t-1} + \rho_{t-1} - \rho_t)}{Sales}$$

The variable θ_t stands for cash flow from operation, ε_t for the accounts receivables, γ_t for inventory, and ρ_t for the accounts payable each at the end of the period. Companies are then selected based on their funds from operation (FFO) margin. This metric is based on the previous year's financial statements, but should still improve the probability that all obligations can be met the following year. The expected fundamental downside protection approach is consistent with Warren Buffet's first rule of investments to "never lose money" as opposed to finding a home run.

The second parameter of the ternary model deals with financial leverage. Leverage may increase market returns and cannot be seen solely as a threat to financial health found Bhandari (1988). It is important, however, to keep risk within certain parameter to avoid bankruptcy cost and impairment of financial flexibility or direct operational impact through illiquidity. While gearing or asset-to-equity leverage ratios provide a reasonable measurement of leverage, the allowance thereof should differ across firms and industries. If Company A has a high gearing ratio but strong cash generating operations, it might be fair to say it runs a similar risk as Company B with a low gearing ratio and difficulties to generate any positive free cash flow. The free cash flow (FCF) to net debt ratio provides the additional feature of firm specific leverage, since a firm with strong cash flows can use more debt financing for the same ratio and the same level of risk measured therein. Therefore the FCF debt coverage ratio is expected to give an allowance for financial leverage. Specifically, since the ternary model emphasizes cash generation, FCF is used for debt coverage purposes to account for capital intensive industries. The model calculates FCF by subtracting capital expenditures from cash from operations. For net debt calculation, the model subtracts the two accounts cash and cash equivalents and marketable securities from total debt outstanding at year end. The last parameter as mentioned earlier will be the price to earnings factor which is calculated by dividing market capitalization by net income attributable to shareholders.

In this experiment, US public companies were screened between 1999 and 2011 and filtered according to the first two parameters of the model which are explained in more details under sample selection and thresholds. The remaining companies are put in a pool from which, in a third step, the twenty companies with the lowest PE ratio are selected. The portfolio is rebalanced once a year, and the proceeds reinvested based on the new year's metrics. The goal of the experiment is to exploit the PE market anomaly and to test whether adding two credit metric screening steps lowers the risk associated with low PE ratios. The risk adjusted returns are measured by the Sharpe ratio and compared to a benchmark consisting of the lowest twenty PE companies every year yet without any previous screening.

Sample selection and thresholds

Using COMPUSTAT as data feed, the stock pool – the list of stocks from which the portfolio is selected – consists of stocks traded either at the NYSE or the NASDAQ. Since neither the FFO margin nor the FCF debt coverage ratio is appropriate to analyze the sectors finance, insurance, real estate or public administration, all companies with Standard Industry Classification Codes (SIC) belonging to these sectors were excluded from the stock pool. 364 different SIC codes were represented in the

stock pool with electric services (4.1%), telephone communications (3.1%) and crude petroleum and natural gas (2.3%) being the largest. A detailed breakdown of the sectors and industries can be found in *Appendix I*. Due to the large number of companies and the more detailed information needed to calculate FFO metrics, the experiment focuses on large US companies (sales over 500 million USD) in order to have consistent extraction of all relevant data. There are a total of 4,722 companies in the stock pool.

In the first step of the model, the minimum FFO / sales threshold was set at 15% in order to cut all companies with insufficient profitability. In order words, each remaining company has 15% of its revenue available in cash for working capital requirements, dividend payments, capital expenditures, debt obligation retirements, acquisitions, share buyback programs etc. After the initial cut in the first step, around 500 companies remained to be selected from in each period.

In step two, all remaining companies are ranked by their respective FCF / net debt ratios. Since the ability to provide sufficient cash flow for sound operations has been tested in step one, all net cash companies are automatically qualified for the last step. All remaining must have sufficient free cash flow to cover their respective net debt within a five year time period; hence, the threshold is set at 20%. Depending on the time period, the number of remaining companies range from 145 to 317. During times of crisis (2001, 2002, 2008, 2009), less companies generated sufficient fund to cover their debt up to the required hurdle rate. The same trend was already observable in step one as FFO margins generally decreased due to a decrease in sales, high fixed costs, or non-rewarding of working capital management.

The third step is designed to select the final stocks from the remaining pool of expected quality stocks using the PE ratio. The 20 stocks with the lowest PE ratios in each time period were selected to be bought equally weighted. *Table I* provides a brief summary of the selection results. The mean FFO margin of 28% shows that the threshold of 15% may have been further amplified by the secondary cash flow requirement in form of the debt coverage by FCF. In this first step, 65% of all companies have been eliminated due to insufficient cash generation. As a reference point, while Kellogg in 2010 barely met the threshold with an FFO margin of 15.4%, a pharmaceutical such as Pfizer easily generated the necessary cash to be considered with a margin of 33.5%. Since the stocks were selected based on the PE ratio, one would expect a lower average than 7.8x. Yet the first two steps contributed to boosting this average by eliminating low PE ratios of distressed firms. The average portfolio PE ratio went as low as 4.8x in 2009 during the financial crisis. Every year, about 18 of the 20 stocks are replaced since the parameters to be met are tough and any stock appreciation will result in a higher PE ratio the following period. Additionally, some companies were subject to takeovers or bankruptcy. The turnover ratios peaked in 2008 and 2009 during the financial crisis. The model turned almost all stocks in 2009 based on the financial positions the different companies were in and their respective valuation, and it recorded a performance of +69% coming out of the crisis as we shall see later. An average FCF to net debt ratio would not be meaningful due to the net cash companies. A more detailed table can be found in *Appendix II*.

Table I

Statistic	Annual average
Selection	
Pool size	1’920
Percentage cut step I	65%
Percentage cut step II	
As a percentage of total pool	90%
As a percentage of post step I pool	47%
Portfolio	
Mean FFO/Sales	28%
Mean PE ratio	7.8x
Turnover	93%

The holding period is set at one year, and every year all stocks are reconsidered going through the same process regardless of whether they have been held in the previous time period leading to the mentioned high portfolio turnover ratio. The return on each individual stock R_i is then calculated as seen below, where D_t stands for any dividend paid during the holding period. Since we rebalance once a year, proceeds from dividends are not reinvested until the new rebalancing.

$$R_i = \frac{p_t + D_t}{p_{t-1}} - 1$$

Results

The performance of the ternary credit metric (TCM) portfolio is summarized in *Table II*. The geometric mean return over the 13 years span of the TCM portfolio is 13.2%. The PE multiple benchmark recorded an annual return of 17.0%, yet experienced much higher volatility. Every dollar invested in the TCM portfolio at inception returned $5.01 by the end of the 13 years period, while the S&P 500 merely returned 131 cents and the benchmark returned $7.69. The Sharpe ratios give a measurement of risk adjusted returns, illustrating how the TCM portfolio reduces risk and still outperforms the general market measured by the S&P 500 index. In the crisis years 2002, 2007 and 2008, the benchmark is hit much harder than the TCM portfolio. This could be partially explained by the defensive preemptive second factor in the model where excessively levered companies are eliminated. A second observation in need of attention is the strong rebound after the crisis, namely in 2003 and 2009. Even though the stock market recovered as a whole, stocks selected based on low multiples performed particularly well during this time periods.

Table II

Year	TCM portfolio	Benchmark	S&P 500
1999	31.3%	9.8%	30.5%
2000	21.7%	57.3%	9.0%
2001	20.3%	49.0%	-2.0%
2002	-10.9%	-16.7%	-17.3%
2003	71.7%	161.8%	-24.3%
2004	24.7%	71.8%	32.2%
2005	24.0%	-0.9%	4.4%
2006	-9.1%	1.3%	8.4%
2007	31.7%	-14.4%	12.4%
2008	-47.8%	-55.9%	-4.2%
2009	68.8%	83.8%	-40.1%
2010	18.6%	20.8%	30.0%
2011	-11.6%	-5.3%	19.8%
Annual return	13.2%	17.0%	2.1%
Sharpe ratio	0.41x	0.30x	0.10x
W&L ratio	1.45x	1.13x	

In order to understand whether the credit metric ternary model excels in picking stocks or whether it merely had a few strong winners, some attention must be paid to the winners / losers (W&L) ratio. It sets the number of stocks in a given period with a positive return relative to the number of stocks with a negative return, where the factor $x = 1$ is assigned to each positive return and the factor $x = -1$ to each negative return and $n = 20$. A ratio above 1.0x implies that more winners than losers have been chosen. The TCM portfolio picked 154 winning stocks relative to 106 losing stocks, while the benchmark only found 138 winning stocks relative to 122 losing stocks. This indicates that the higher return of the benchmark is mainly attributable to a few exceptional performances of a few stocks. Indeed when looking at each individual investment, the TCM model's investments have a mean return

of 17.9% and a median 7.9%, while the benchmark reports 27.8% and 5.0% for the same figures respectively (see *Appendix III*). This is a strong indication that the benchmark's performance can be explained by a few extraordinary investments which distort the median return upwards. As expected, the TCM model's investments' volatility of 73.1% is accordingly lower than the benchmark's 137.9%. This further explains the higher risk adjusted returns of the TCM model.

$$Winner\ /\ Looser\ ratio = \frac{\sum_{j=1}^{n}\{1|x>0\}}{\sum_{j=1}^{n}\{1|x<0\}}$$

Initially the argument was made, that low PE multiples increase the likelihood of investing in a distressed company, hence, both the benchmark and the TCM portfolio must be analyzed for any such event. *Table III* summarizes all bankruptcy events in both portfolios, and how bankruptcies in the benchmark were eliminated if at all. While the TCM portfolio investments ended in bankruptcy merely 3 times over the 13 years, the PE benchmark lost money in 22 bankruptcies. Out of this 22 bankruptcies, the TCM model detected 20 using both steps. The FFO margin found 17 while the debt coverage ratio would have found 13. This is a nice illustration of the power of using credit metrics to test low multiples for financial soundness of the underlying company.

Table III

	TCM portfolio	Benchmark
	Bankruptcy occurrences	
Chapter 11	3	19
Chapter 7	0	3
% of stocks ending in bankruptcy	1.2%	8.5%
	Benchmark bankruptcies eliminated by the TCM steps	
FFO margin only		7
Debt coverage only		3
Joint detection		10
Missed bankruptcies		2

To understand whether the TCM model works, the industry allocation must be analyzed as well. High margins and particular FCF / debt ratios may stir the investments toward a particular sector creating a corner portfolio. Returns would then mainly depend on the performance of such a sector. A detailed analysis of the underlying sector performance of the data set is included in *Appendix I***.** The only sector that is strongly overweighed in the portfolio relative to the weighting in the underlying data set is the mining sector (+14.8%). This particular sector happened to outperform all others sector, yet a regression analysis shows that H_0 = *sector weights explain returns* can be rejected at the 95% confidence level. All other weightings seem randomly chosen. The only sector with negative annualized performance is the agricultural, forestry and fishing sector (-2.3%), and its respective weight in the portfolio is equivalent to the sector's representation in the stock pool.

Regression

The positive aspect of finding mergers, acquisitions and bankruptcies in a data set is that it proves that there is no survivorship bias, since companies that did not survive are included in the data. Yet looking up each event to understand what happened to the investment can be time consuming. Over 1000 such events are found in the data set, which makes a regression analysis over the entire set difficult. Accordingly a randomly chosen year (2003) shall be used to conduct some further tests.

All regression analysis tests can be found in *Appendix IV***.** First thing to be tested is whether low PE multiples result in more bankruptcies. Even though the R^2 is 1.94%, the regression coefficient is significantly different from zero at the 99% confidence level. This can be interpreted as low multiples having some explanatory power for bankruptcies, even though the correlation is only 0.14. Having found that, I tested whether the TCM model improves returns and detects bankruptcies. Among the three factors PE, FFO margin and debt coverage, only the PE ratio has a significant explanatory power for returns. Single factor regressions show that the use of FFO margins can decrease the number of bankruptcies invested in (p-value = 0.0054), yet the debt coverage ratio fails to significantly detect bankruptcies on a standalone basis (p-value = 0.1344). Using a multiple regression analysis though shows that the combined steps FFO margin and FCF debt coverage ratio are significantly contributing at the 99% confidence level using an F-test. This should not surprise, considering that 20 out of the 22 bankruptcies of the benchmark fund were detected.

Conclusion

This research paper examined whether a ternary credit metric (TCM) model can select a portfolio of 20 stocks based on valuation multiples (PE ratio) and credit metrics, which then outperforms a benchmark based solely on low multiples as well as the S&P 500 index. The performance over the 13 year span was measured by the Sharpe ratio to examine the risk adjusted returns. The economic intuition that low multiples reflect higher risk was addressed by the TCM model using a dual elimination process to ensure sufficient liquidity at the underlying operation of each selected security. The two metrics FFO margin and debt coverage ratio successfully improved risk adjusted returns both relative to the benchmark and the S&P 500. The portfolio selected by the ternary model significantly outperformed the S&P 500, returning $ 5.01 at the end of the experiment for every dollar invested at inception (13.2% p.a.). The benchmark had slightly higher unadjusted returns, yet the Sharpe ratio for the TCM portfolio was 0.41, compared to 0.30 and 0.10 for the benchmark and the S&P 500 index, respectively.

Financial distress among the invested companies was also measured by examining how many investments ended in bankruptcy. While the TCM portfolio only encountered three bankruptcy cases over the 13 years, a portfolio based solely on low multiples lost money in 22 bankruptcies. Out of these 22 bankruptcies, the TCM model avoided 19, therefore significantly reducing the probability of investing in financially distressed companies – a risk often associated with low multiples. In a further sample examination, the TCM model's first and second elimination step were regressed against bankruptcy occurrences (binominal variable) to test the robustness on a larger scale. According to the regression analysis, the hypothesis that the TCM's preliminary screening significantly reduces the risk of bankruptcy investments cannot be rejected (p-value of 0.0100).

With regards to security return predictability, David Hirshleifer said cautious skepticism rather than profound suspicion is called for. On this note, further tests can be conducted before implementing this investment strategy, since this analysis was focused on the argument by efficient market theory advocates that low PE ratios merely represent more risky stocks. Such additional tests include a measurement of explicit and implicit trading costs (e.g. liquidity of small cap to cover a 20^{th} of the portfolio), an examination of an extended time period going forward, as well as profound tests of the data stream from COMPUSTAT, as certain companies have been prematurely eliminated due to a lack of streamed data.

Appendix I

Breakdown of the stock pool into nine sectors and 364 industries after deduction of financial and government administration sector which accounted for about 12.8% of all stocks.

Sector breakdown

Sector	Pool weights	Portfolio weights	Over / (Under)	Return p.a.
- Agriculture, Forestry & Fishing	0.3%	0.8%	0.5%	-2.3%
- Mining	4.8%	19.6%	14.8%	10.7%
- Construction	1.8%	2.3%	0.5%	4.9%
- Manufacturing	41.5%	49.2%	7.8%	4.0%
- Transportation, Communications, Electric, Gas & Sanitary Services	20.8%	14.2%	-6.5%	3.7%
- Wholesale Trade	5.7%	0.8%	-4.9%	5.5%
- Retail Trade	10.4%	2.7%	-7.7%	4.7%
- Services	14.8%	10.4%	-4.5%	2.2%

Industry breakdown (Top 20)

SIC	Industry	Companies	% / total	Cumulative
4911	Electric Services	168	4.1%	4.1%
4813	Telephone Communications	126	3.1%	7.1%
1311	Crude Petroleum & Natural Gas	96	2.3%	9.5%
3674	Semiconductors & Related Devices	84	2.0%	11.5%
4931	Electric & Other Services Combined	79	1.9%	13.4%
7372	Services-Prepackaged Software	78	1.9%	15.3%
4812	Radiotelephone Communications	74	1.8%	17.1%
2834	Pharmaceutical Preparations	68	1.7%	18.8%
2911	Petroleum Refining	66	1.6%	20.4%
5411	Retail-Grocery Stores	64	1.6%	21.9%
7370	Services-Computer Programming, Data Processing	60	1.5%	23.4%
3312	Steel Works, Blast Furnaces & Rolling Mills	57	1.4%	24.8%
5812	Retail-Eating Places	57	1.4%	26.2%
3714	Motor Vehicle Parts & Accessories	52	1.3%	27.4%
7373	Services-Computer Integrated Systems Design	47	1.1%	28.6%
4512	Air Transportation, Scheduled	41	1.0%	29.6%
4841	Cable & Other Pay Television Services	41	1.0%	30.6%
7990	Services-Miscellaneous Amusement & Recreation	37	0.9%	31.5%
2860	Industrial Organic Chemicals	33	0.8%	32.3%
4922	Natural Gas Transmission	33	0.8%	33.1%

Appendix II

Appendix II shows how many companies out of the available in the pool were cut in each step.

Pool size

Year	Pool size	Step I cut (% of total)	Step II cut (% of total)	Step II cut (% post step I)
1999	1715	68%	94%	55%
2000	1790	68%	94%	57%
2001	1827	70%	94%	51%
2002	1914	72%	95%	53%
2003	1921	66%	93%	50%
2004	1942	64%	91%	46%
2005	1974	61%	88%	42%
2006	1979	66%	89%	40%
2007	2005	63%	87%	43%
2008	1988	60%	87%	44%
2009	2038	66%	89%	49%
2010	1979	62%	88%	43%
2011	1884	68%	84%	42%

Appendix III

Appendix III shows the how the individual investments in the TCM portfolio and the benchmark differ in terms of how many stocks have been acquired or canceled in bankruptcy. Interesting is that 8.5% of all investments in the benchmark ended in bankruptcy while only 1.2% of all investments of the TCM portfolio did so.

Portfolio statistic	Ternary Model	Benchmark	S&P 500
	Total portfolio		
Annual portfolio return	13.2%	17.0%	2.1%
Annual portfolio volatility	32.0%	56.4%	22.0%
Sharpe ratio	0.41	0.30	0.10
Win / Loss ratio	1.45x	1.13x	
Winner : Loser	(154:106)	(138:122)	
	Per investment		
Mean return	17.9%	27.8%	
Median return	7.9%	5.0%	
Volatility	73.1%	137.9%	
Mean top 10	234.4%	551.2%	
Mean bottom 10	-88.2%	-100.0%	
	Events		
Investments bought in M&A transaction	10	16	
% of all investments	3.8%	6.2%	
Chapter 11	3	19	
Chapter 7	0	3	
% investments ending in bankruptcy	1.2%	8.5%	

Appendix IV

ANOVA – PE multiples regressed against bankruptcies (binary)

Source of Variation	Df	SS	MS	F-test	P-value
Regression	1	0.2309	0.2309	26.32	0.0000
Residual	1'329	11.6609	0.0088		
Total	1'330	11.8918			

R^2 = 1.94%

Parameter	Coefficients	Standard Error	t Stat	P-value
Intercept	0.028	0.005	6.22	0.0000
PE ratio	-.0001	0.000	-5.13	0.0000

ANOVA – FFO margin regressed against bankruptcy (binary)

Source of Variation	Df	SS	MS	F-test	P-value
Regression	1	0.1124	0.1124	7.7687	0.0054
Residual	1'329	19.2277	0.0145		
Total	1'330	19.3401			

R^2 = 0.58%

Parameter	Coefficients	Standard Error	t Stat	P-value
Intercept	0.016	0.004	4.43	0.0000
FFO margin	-0.060	0.021	-2.79	0.0054

ANOVA – FCF / Net debt regressed against bankruptcies (binary)

Source of Variation	Df	SS	MS	F-test	P-value
Regression	1	0.0200	0.0200	2.2432	0.1344
Residual	1'329	11.8718	0.0089		
Total	1'330	11.8918			

R^2 = 0.17%

Parameter	Coefficients	Standard Error	t Stat	P-value
Intercept	0.012	0.003	3.67	0.0003
FCF / Net debt	-0.004	0.003	-1.50	0.1344

ANOVA – FFO margin regressed against return

Source of Variation	Df	SS	MS	F-test	P-value
Regression	1	1.2755	1.2755	3.6426	0.0565
Residual	1'329	465.3759	0.3502		
Total	1'330	466.6514			

R^2 = 0.27%

Parameter	Coefficients	Standard Error	t Stat	P-value
Intercept	21.46%	2.30%	9.32	0.0000
FCF / Net debt	-25.68%	13.46%	-1.91	0.0565

ANOVA – FCF / Net debt regressed against return

Source of Variation	Df	SS	MS	F-test	P-value
Regression	1	0.8150	0.8150	2.3250	0.1275
Residual	1'329	465.8364	0.3505		
Total	1'330	466.6514			

R^2 = 0.17%

Parameter	Coefficients	Standard Error	t Stat	P-value
Intercept	20.24%	2.05%	9.88	0.0000
FCF / Net debt	-2.77%	1.82%	-1.52	0.1275

ANOVA – Multi-Regression all parameters regressed against return

Source of Variation	Df	SS	MS	F-test	P-value
Regression	3	3.5155	1.1685	3.3479	0.0185
Residual	1'327	463.1559	0.3490		
Total	1'330	466.6514			

R^2 = 0.75% and adj. R^2 = 0.53%

Parameter	Coefficients	Standard Error	t Stat	P-value
Intercept	26.92%	3.16%	8.53	0.0000
FFO margin	-16.76%	13.90%	-1.21	0.2280
FCF / Net debt	-1.79%	1.85%	-0.97	0.3338
PE ratio	-0.31%	0.14%	-2.15	0.0320

ANOVA – FFO margin and debt coverage regressed against bankruptcy (binary)

Source of Variation	Df	SS	MS	F-test	P-value
Regression	2	0.0822	0.0411	4.6243	0.0100
Residual	1'328	11.8096	0.0089		
Total	1'330	11.8918			

R^2 = 0.69% and adj. R^2 = 0.54%

Parameter	Coefficients	Standard Error	t Stat	P-value
Intercept	1.84%	0.41%	4.53	0.0000
FFO margin	-5.70%	2.16%	-2.64	0.0083
FCF / Net debt	-0.35%	0.29%	-1.22	0.2244

Appendix V

Below are the different codes used to source the accounts needed from COMPUSTAT. (Alphabetic order)

Code	Account	Code	Account
AP	Accounts payable	MKVALT	Market capitalization
CAPX	Capex	NI	Net income
CHE	Cash & cash equivalent	OANCF	Cash flow from operations
DLC	Current debt	PRCC_C	Price close
DLTT	Long term debt	RECT	Accounts receivable
INVT	Inventory	REVT	Revenue

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