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The Importance of Profitability in Determining Volatility Across Industries with Different Debt Levels

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Abstract

This paper seeks to investigate the relationship between debt and volatility. No consensus currently exists on the effects of financial leverage on stock volatility. With the increased use of complex financial derivatives in recent decades, the importance of understanding the factors that influence volatility has become extremely important. By looking at a cross-section of industries, this paper demonstrates how the importance of profitability for explaining volatility changes depending on industry debt levels, which are endogenous and depend on industry characteristics.

Keywords

Volatility, Debt, Profitability

1. Introduction

The effects of debt on firm value are well understood through past research, such as the Modigliani-Miller propositions[1]. These propositions provide a framework for a firm manager to decide the capital structure of a firm. Taking on more debt provides a benefit of an interest tax shield, but the trade-off comes from increasing costs of financial distress as the firm's debt level increases. Given the idiosyncrasies of each firm, debt levels vary widely across firms.

Unlike for firms, at an industry level there exists an optimal debt level that best balances these benefits and costs of debt, due to the structural characteristics of each industry. For example, software companies tend to carry little debt, with an average debt to capital ratio of 4% (in my sample), because they tend to have smaller balance sheets and less collateral. On the other hand, utilities companies have bigger balance sheets and consequently carry much more debt, with an average debt to capital ratio of 42% (in my sample). This paper seeks to investigate the question of whether or not there exists a third factor that is affected by debt level – stock price volatility. No consensus currently exists on the effects of financial leverage on stock volatility. With the increased use of complex financial derivatives in recent decades, the importance of understanding the factors that influence volatility has become extremely important. Implied volatility is a key factor in the pricing models of these derivatives, meaning that if an investor has an edge in volatility forecasting, he or she will be able to generate excess returns.

The significance of financial leverage on volatility, at an industry level, has not previously been investigated. This paper looks to address the question of what key factors are important for determining volatility across industries. This is done through splitting the sample industries into two groups, low debt and high debt, and examining how the effects of profitability, competitiveness, and systematic risk level differ. In doing so, I find that net margin plays a more significant role in predicting volatility for high debt industries than low debt industries.

2. Literature Review

As aforementioned, there is no agreement on the effect of debt levels on stock price volatility. Christie (1982) was one of the first to look at the question. He found empirical evidence of a negative relationship between stock returns and volatility,

[1] These propositions lead to the conclusion that in choosing an optimal debt level, a firm must balance the benefits of an interest tax shield with the costs of financial distress associated with more debt.

induced by financial leverage at the firm level (the so-called "leverage effect"). Other papers such as Schwert (1989) and Figlewski and Wang (2000) expanded upon Christie's research, looking at how the strength of this effect differs across firms of different sizes, and on the market as a whole. Aydemir, Gallmeyer, and Hollfield (2007) wrote the most recent paper on this topic. However, they investigated how the size of the "leverage effect" at the firm and market level differed in between two economies: a static economy with constant interest rates and market risk premium, and a dynamic economy that generates time-variation in these factors. Their results show that the leverage effect is insignificant at the market level in both economies, significant at the firm level in a static economy, and significant for only small firms in a dynamic economy.

Unlike the past research, this paper focuses on analyzing the effects of debt on stock volatility through profitability rather than stock returns. It is well understood that profitability should be inversely related with volatility because less margin[2] means less consistent earnings for equity holders. However, what hasn't been previously studied is how the importance of profitability increases as a firm's debt level increases. This is because as debt levels increase, the costs of financial distress become more eminent. If a higher debt company is not profitable, after the many debt payments there is nothing left over for equity holders, making their returns more volatile.

3. Data Description

The data used in this paper comes from Aswath Damodaran, Ph.D[3]. The two datasets used are titled *Levered and Unlevered Betas by Industry* and *Price and Value to Sales Ratios and Margins by Industry Sector*. Both datasets contain data on the U.S. only and are purely cross-sectional. There are 94 observations in each dataset, where each observation corresponds to 1 of 94 industries. In order to conduct the following analysis, the two datasets were merged together based on ***Industry Name***.

The main limitation of this dataset is the small number of observations. Consequently, I cannot take advantage of the asymptotic properties of different estimation procedures, such as ordinary-least squares and generalized-least squares. Moreover, in an ideal world I would like to have more financial statistics for each industry to allow for a wider range of measures for profitability, systematic risk,

[2] In this paper, profitability will be measured by Net Margin, which equals Net Income/Sales.
[3] Data can be found at http://pages.stern.nyu.edu/~adamodar/New_Home_Page/home.htm. Aswath Damodaran is a Professor of Finance at NYU Stern.

and competitiveness. However, I am limited to the data available on this website because Professor Damodaran defines each industry in a particular way. Since every data source defines industries differently, I must exclusively use data from one website to ensure consistency in our dataset.

The two datasets mentioned above contain many different variables. In merging the datasets, I focused on the following five statistics: ***Number of Firms, Equity Vol, Net Margin, Beta,*** and ***D/(D+E)***. A shortened version of the dataset is shown in Table 1 and Table 2 contain summary statistics.

Below are the definitions for each variable[4]:

- ***Industry Name***: the name of the industry
- ***Number of Firms***: the number of firms represented in each industry
- ***Equity Vol***: annualized standard deviation in weekly stock prices over the past two years
- ***Net Margin***: cumulative income of industry divided by cumulative sales of industry
- ***Beta***: levered equity beta from market model regression against S&P 500 using past two years of data
- ***D/(D+E)***: the market value estimate of the debt ratio, obtained by dividing the cumulated value of debt by the cumulated value of debt plus the cumulated market value of equity for the entire industry

4. Econometric Model and Analysis

Before investigating the effects of debt on stock price volatility, I ran the following baseline specification containing all other regressors:

$$(1)\ Equity\ Vol = \beta_0 + \beta_1 * Number\ of\ firms + \beta_2 * Beta + \beta_3 * Net\ Margin + \varepsilon$$

The results from this regression and all other regressions in this section can be found in Table 3 according to their corresponding specification number. The three explanatory variables in (1) appear to have significant effects in predicting stock volatility. Next, I ran specification (2) to investigate the effect of debt:

$$(2)\ Equity\ Vol = \beta_0 + \beta_1 * Number\ of\ firms + \beta_2 * Beta + \beta_3 * Net\ Margin +$$

[4] These definitions are taken from: http://people.stern.nyu.edu/adamodar/New_Home_Page/datafile/variable.htm.

$$\beta_4 * D/(D+E) + \varepsilon$$

The coefficient estimate on ***D/(D+E)*** for (2) shows a similar result to what has been found in previous literature, namely that higher levels of debt are associated with lower levels of volatility. The coefficients on the other regressors that were in (1) were still significant with the introduction of ***D/(D+E)*** in (2). Specification (2) contains ***Beta*** and ***Net Margin***, which are measures of systematic risk and profitability, respectively. To further investigate the effect of debt levels, I split the data set into two: the industries with a debt level less than median of the 94 industries (0.26), and those with a debt level greater than the median. I refer to these groups as *Low Debt* and *High Debt*. Specification (3) represents the same model as (2), except the sample is restricted to *Low Debt* industries. Similarly, specification (4) represents the same model as (2), except the sample is restricted to *High Debt* industries.

Comparing specifications (3) and (4) shows that ***Net Margin*** appears to be significant[5] for *High Debt* industries, but very far from significant for *Low Debt* industries. In order to create a model that allows for different slope estimates ***Net Margin*** for *Low Debt* and *High Debt* industries, I created the following two dummy interactions and ran specification (5):

Low Debt Net Margin* =** Industry's ***Net Margin * LD, LD = {1 if industry is *Low Debt*, 0 otherwise)

High Debt Net Margin* =** Industry's ***Net Margin * HD, HD = {1 if industry is *High Debt*, 0 otherwise)

$$(5) \qquad Equity\ Vol = \beta_0 + \beta_1 * Number\ of\ firms + \beta_2 * Beta + \beta_3 * Low\ Debt\ Net\ Margin + \beta_4 * High\ Debt\ Net\ Margin + \varepsilon$$

The results of specification (5) further demonstrate the result that a ***Net Margin*** plays a much larger and more significant role for high debt industries than low debt industries. Before discussing the results further, I will perform some tests and corrections to demonstrate the robustness of this effect.

Chart 1 contains a graph of the residuals against the fitted values. As the trend line demonstrates, specification (5) has an issue with heteroscedasticity. More formally,

[5] All significance tests are done at the 5% level.

running a Breusch-Pagan test[6] results in rejecting the null of homoscedasticity at the 2.9% level. To address this problem, I pursed the following three solutions:

1. Re-estimate the variance-covariance matrix using White's technique, resulting in new standard errors that are commonly known as White standard errors.
    a. The results of this correction are in Table 3 as specification (6).
2. Run a more efficient estimator known as *generalized-least squares* under the assumption of multiplicative heteroscedasticity[7].
    a. The results of this estimation are in Table 3 as specification (7).
3. Re-specify the dependent variable in log-form.
    a. The results of the following specification are in Table 3 as specification (8).

$$\log(Equity\ Vol) = \beta_0 + \beta_1 * Number\ of\ firms + \beta_2 * Beta + \beta_3 * Low\ Debt\ Net\ Margin + \beta_4 * High\ Debt\ Net\ Margin + \varepsilon$$

To confirm the effectiveness of solutions 2 and 3, I ran a Breusch-Pagan test on (7) and (8). Both models resulted in a failure to reject the null of homoscedasticity at any reasonable level.

Lastly, I ran a third-order RESET test[8] for functional form misspecification on the FGLS model. This resulted in a failure to reject the null of second or third order functional form misspecification due to t-stats of 0.15 and 0.2 on the squared and cubed fitted values from (7), respectively, in the auxiliary regression.

5. Results

Given FGLS is the most active solution to heteroscedasticity, I believe specification (7) most accurately describes the data-generating process that I seek to describe.

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[6] The Breusch-Pagan test was conducted using the bptest() function in R, which runs the commonly known Breusch-Pagan test under the null of homoscedasticity.

[7] This is also known as *Feasible Generalized-Least Squares.* The process is as follows:

1. Run specification (5).
2. Collect the residuals.
3. Run an auxiliary regression of the log(*residuals*^{2}) on all regressors.
4. Collect the fitted values and compute h = sqrt($e^{\text{fitted values}}$), where h is a (94 x 1) vector.
5. Run *generalized-least squares* with the weights 1/h.

[8] By third-order, I mean that in the auxiliary regression contains the fitted values from the specification (7) raised to the second and third powers.

Moreover, specification (7) likely does not suffer from functional form misspecification due to the failure to reject the null in the RESET test.

Comparing the significance of ***Low Debt Net Margin*** and ***High Debt Net Margin*** in specification (7) demonstrates the key result of this paper, namely that ***Net Margin*** is a key determinant of stock volatility for *High Debt* industries, but not *Low Debt* industries. An increase of ½ a standard deviation (6.5 percentage points) in a *High Debt* industry's net margin will result in approximately a 1.4 percentage point decrease in its stock price volatility, holding its level of systematic risk and size constant. Meanwhile, the estimates of ***Low Debt Net Margin*** are not significant in any of the regression specifications in Table 3. These results demonstrate that for higher debt industries, profitability becomes of vital importance to reduce volatility because otherwise after interest payments there is nothing left over for equity holders.

Moreover, in almost every specification ***Number of Firms*** is significant with a positive coefficient. This suggest that competitiveness of an industry plays a role in determining equity holders' earnings volatility. With more firms in an industry, there is a greater fight for market share, which in turn appears to increase volatility.

One potential issue that could affect these results is the low number of observations in the dataset because White standard errors and FGLS are both only justified in large samples. However, I tried to address this problem by logging the dependent variable and running specification (8) to address the heteroscedasticity. The results of this specification demonstrate a similar story in terms of relative significance of ***Low Debt Net Margin*** and ***High Debt Net Margin***, providing further evidence of the effect of debt on volatility through profitability.

6. Conclusion

Understanding the determinants of volatility in a world full of complex financial instruments is increasingly important. My results show that for higher debt industries, profitability plays an important role in determining earnings volatility. The costs of financial distress become looming with more debt, making profitability crucial to maintaining low equity volatility. To further investigate this relationship, further studies should be done that look at the effect on a firm level and incorporate some amount of time-variation.

7. Tables and Charts

Table 1

Industry Name	Equity Vol	Net Margin	Beta	Number of firms
Software (Internet)	0.56	0.13	1.13	297.00
Retail (Online)	0.49	0.03	1.23	57.00
Shoe	0.37	0.10	0.85	10.00

Table 2

Summary Statistic	Number of firms	Equity Vol	Net Margin	Beta	D/(D+E)
Mean	73.07	0.43	0.06	1.00	0.44
Standard Deviation	95.65	0.18	0.17	0.29	1.12
Median	39.50	0.44	0.06	1.04	0.28

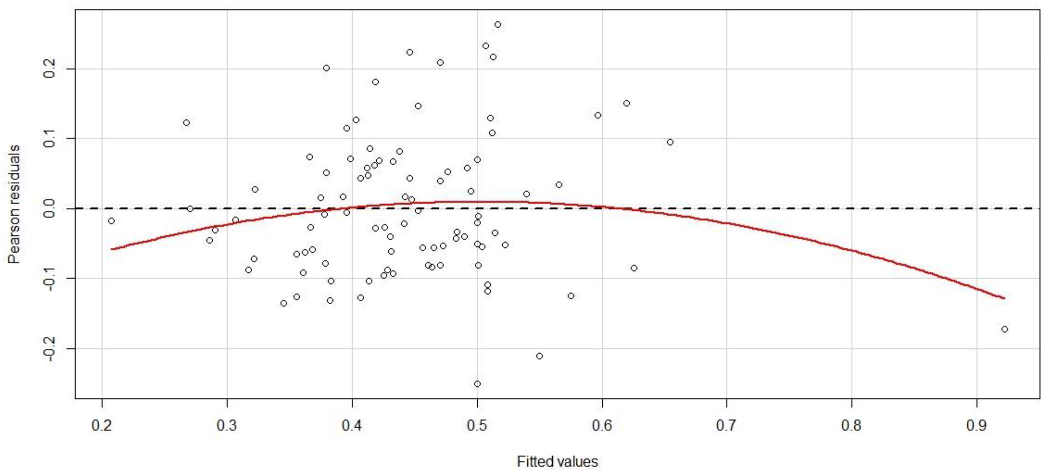
Table 3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable = ***Equity Vol***						
Technique	OLS	OLS	OLS	OLS	OLS	OLS, White	FGLS
Intercept	0.11	**0.18**	**0.21**	0.14	**0.12**	**0.12**	0.12
	(0.06)	(0.06)	(0.09)	(0.08)	(0.06)	(0.06)	(0.06)
Number of Firms	**0.00030**	**0.00027**	**0.0006**	0.00005	**0.0003**	**0.0003**	**0.0003**
	(0.00010)	(0.00010)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Beta	**0.31**	**0.29**	**0.21**	**0.28**	**0.30**	**0.30**	**0.29**
	(0.05)	(0.05)	(0.08)	(0.07)	(0.05)	(0.055)	(0.05)
Net Margin	**-0.26**	**-0.29**	-0.19	**-0.37**			
	(0.09)	(0.09)	(0.21)	(0.11)			
D/(D+E)		**-0.15**					
		(0.07)					
Low Debt Net Margin					0.02	0.02	0.06
					(0.17)	(0.23)	(0.17)
High Debt Net Margin					**-0.35**	**-0.35**	**-0.22**
					(0.10)	(0.15)	(0.07)
R-Squared	0.44	0.47	0.37	0.57	0.47	0.47	N/A
RMSE	0.105	0.103	0.102	0.102	0.103	0.103	0.026

	(8)
	Dependent Variable = log(***Equity Vol*** *)*
Technique	OLS
Intercept	**-1.67**
	(0.13)
Number of Firms	**0.0005**
	(0.0002)
Beta	**0.75**
	(0.12)
Low Debt Net Margin	0.31
	(0.40)
High Debt Net Margin	**-0.67**
	(0.23)
R-Squared	0.47
RMSE	0.237

*Bold coefficient estimates mean they are significant at the 5% level

Chart 1 – Residuals plot demonstrating heteroscedasticity



8. Acknowledgments

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