Uncertainty, stock returns and shareholder value

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Received January 2008

Abstract

Recent studies by Diether et al. (2002) and Johnson (2004) provide evidence of a negative relation between dispersion in analyst forecasts and stock returns, being particularly pronounced for the levered firm. Both suggest that their findings indicate a positive impact of dispersion in analyst estimates on shareholder value, offering different explanations. I complement their work by analyzing the relationship between information uncertainty measured by analyst dispersion and coverage on the one hand and simple measures of excess value based on multiple valuation on the other. In contrast to previous reasoning, I find a negative relation between analyst dispersion on the one hand and credit quality as well as excess value on the other. The aggregate evidence indicates that intransparency decreases shareholder value, possibly due to intensified agency problems. On a more general level, my results shed light on the relation between return and shareholder value and caution academics to interpret low stock returns as evidence for highly-priced securities.

Keywords: Agency costs, Asymmetric information, Transparency, Reverse asset substitution, Shareholder Value
JEL classification: G12, G14

⋆ The author would like to thank Yakov Amihud for helpful comments. All remaining errors are, of course, my own.
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1 Introduction

In their intriguing article, Diether et al. (2002) (henceforth DMS) report that "stocks with higher dispersion in analyst forecasts earn lower future returns than otherwise similar stocks." They interpret their finding as evidence for the model of Miller (1977) according to which securities are overpriced when investors with the lowest valuations do not trade.

Building upon the study of DMS, Johnson (2004) finds that the negative relation between dispersion and future returns disappears when introducing leverage and the interaction term leverage×dispersion into a Fama-MacBeth regression model. He argues that, "for levered firms, adding idiosyncratic uncertainty about cash flows increases the option value of equity. In fact, the situation is exactly analogous to the so-called asset substitution agency problem in corporate finance, except that here a separate-and much simpler-channel is involved. No assets need be substituted to achieve the desired result. All that is required is obfuscation." And further claims that his "model does not invoke any market frictions or irrationality."

I argue that the interpretation of his findings is flawed for several reasons and offer a different explanation.

Three main concerns about his results are highlighted in the following.

First, a transfer of wealth from debt to equity holders assumes that debt holders recurringly underestimate the cost of debt when negotiating debt contracts. In the case of obvious and non sudden information risk, even a non-recurring underpricing of information risk seems to be a rather strong assumption. The notion that creditors price uncertainty is supported by my finding of a negative relation between dispersion and firm rating.

Second, even if debt holders could be assumed to be naïve, an increase in idiosyncratic risk would lead to a premium in the price for stocks with high dispersion as compared to low dispersion due to higher future cash flows, but NOT to lower returns. In an efficient market setting, shareholders predicting a wealth transfer would only bid up the price up to the price where they obtain a "fair" return.

Third, if - as argued by Johnson - in fact no risk shifting takes place, actual firm risk is not altered, just obscured. Higher option prices are thus not justified by any means in a rational framework.

I complement the research by DMS and Johnson (2004) by analyzing the relationship between uncertainty measured by dispersion in analyst estimates and analyst coverage on the one hand and simple measures of excess value based on multiple valuation on the other. In contrast to previous arguments about the benefits of uncertainty, I find a positive relation between dispersion and credit risk and a negative relation between excess value and dispersion. The evidence provided in this paper strongly suggests that high analyst dispersion - being a proxy for uncertainty and information asymmetry - does not create shareholder value. On a more general level, academics are cautioned against interpreting abnormally low long run returns as evidence for high priced securities.

The remainder of the paper is organized as follows. Section 2 describes data and sample selection procedure. Section 3 presents support for the work of DMS, showing the validity of DMS´ results even under stricter sample selection criteria. Section 4 contains the central empirical results of this paper, reporting evidence for a positive relationship between analyst dispersion and the cost of debt, as well as a negative relationship between analyst dispersion and shareholder value. Section 5 concludes.

2 Data and Sample Selection

The primary data sources used for this study are the Center for Research in Security Prices (CRSP) Monthly Stocks Combined File, the Compustat Segment Information File, the Compustat Industrial Annual File, as well as the Institutional Brokers Estimate System (I/B/E/S) Unadjusted Detail History File. The sample covers the period starting January 1984 and ending December 2005. [1]

In order to compute dispersion in analyst forecasts, each firm-month observation included in the sample is required to have an analyst coverage of at least two reported in the Unadjusted I/B/E/S Detail History database. Following DMS I rely on unadjusted data in order to avoid potential biases due to stock splits and rounding errors. [2] An initial sample of 1.71 million firm-month-analyst observations is increased by 3.14 million observations by extending all analyst forecasts from the month they were first issued until their last revision date, i.e. the date they were last confirmed by the analyst. This can be regarded as the conservative approach as compared to the summary files. As argued by DMS, this avoids the inclusion of analyst estimates which are no longer current, thus avoiding an upward-bias in dispersion es-

[1] No observations before January 1984 are included because no reliable SIC codes are available on segment level from Compustat until then. Those are required for peer-group based valuation.

[2] See DMS, p.2117

timates. Based on the aggregated 4.85 million firm-month-analyst estimates, analyst dispersion is computed for 501,572 firm-month observations. [3]

Monthly stock return data must be available from CRSP for the month following a firm-month dispersion data-point. Following Jarrow (2001), observations with a share price below 5 USD are excluded in order to avoid a potential liquidity bias.

Finally, a measure of excess value first derived by Berger and Ofek (1995) (henceforth BO) must be computable. More specifically, firms included in the analysis are required to have (i) net sales of at least 50 million USD, (ii) SIC codes available for all segments with assets reported to be above zero, (iii) the sum of total assets reported on segment level not deviating more than 25% of the firm´s total assets and (iv) no segments active in the financial services industry (SIC codes between 6000 and 6999).

The final sample consists of 264,710 firm-month observations.

3 Analyst Dispersion and the Cross Section of Stock Returns

In a first step, I replicate the results of DMS, confirming the robustness of their analyses to the variations in sample selection criteria described above. Each month, I assign all stocks included in the sample to 25 portfolios based on the quintile of their market-capitalization (controlling for potential size effects) and the quintile of their analyst dispersion of the previous month. Analyst dispersion DISP is defined as the standard deviation of analysts‘ prediction of firm i‘s earnings per share in the

[3] For details, see the subsequent section.

next year (EPS1), divided by the mean analyst forecast for that firm:

$$\mathrm{DISP_i} = \frac{\sigma(\mathrm{E[EPS1_i]})}{Average(\mathrm{E[EPS1_i]})} \tag{1}$$

where E[EPS1] is a vector of all 1-year analyst earnings forecasts for firm i reported in I/B/E/S. Stocks of firms with an average EPS1 estimate equal to zero are assigned to the highest dispersion quintile.

As reported in table 1, I find a negative relation between DISP and monthly stock returns. My results are in line with findings reported in previous literature.

[Table 1 about here.]

4 Analyst Dispersion, Credit Quality and Shareholder Value

The main objective of this paper is to demonstrate that the hypothesis uncertainty and information asymmetry - proxied by dispersion in analyst forecasts - increase shareholder value put forth in previous research has to be dealt with carefully.[4] Abnormally low returns which can not be explained by low risk connected to an investment do indicate overpricing. However, this does not necessarily imply that securities are valued higher than their peers and neither should be interpreted as the creation of shareholder value.

In contrast to Johnson (2004), I argue that higher uncertainty about the magnitude

[4] According to Johnson (2004) “for levered firms, adding idiosyncratic uncertainty about cash flows increases the option value of equity.´´

of future cash flows increases the cost of debt and decreases shareholder value.

4.1 Measuring Excess Value

While the cost of debt is simply proxied by credit rating, deriving a measure for shareholder value requires a more sophisticated approach. I derive a measure for the excess value of firms by extending a part of the methodology used by BO. They compute excess value as the natural logarithm of the ratio of a conglomerate's market value to its imputed value. The latter equals the cumulated value of its business segments. A segment's value is derived by applying the median valuation multiple of an industry peer group of single segment firms to the corresponding accounting item of the segment. Using this procedure, BO present evidence for a conglomerate discount derived based on the accounting items assets, sales, and earnings before interest and taxes (EBIT). Given that valuation using profitability based multiples can produce noisy results, I restrict the analysis presented in the following to the use of asset multiples.

Following BO, I assign valuation multiples to the business segments of each firm in a first step. Those are calculated as the median ratio of total capital (being defined as the market value of common equity plus the book value of total debt) to total assets of at least five single-segment firms operating in the same industry as the business segment. Starting with an industry definition based on the four-digit SIC code, this criterion is broadened to the first three and thereafter the first two digits in case no five matching firms can be found on the narrower level. In doing so, I derive the imputed value of 55.7% of the segments based on four-digit, 21.7% on three-digit and 22.6% on two-digit industry peers. In a second step, I apply those multiples to the sales of companies' business segments, yielding the segments' imputed values and then derive the excess value as explained above as

$$\mathrm{IV} = \sum_{i=1}^{n} \mathrm{TotalAssets}_i M_i, \tag{2}$$

$$\mathrm{EV}_1 = \ln\left(\frac{V_i}{\mathrm{IV}_i}\right), \tag{3}$$

where IV denotes the imputed value of firm segments as standalone firms, $\mathrm{TotalAssets}_i$ denotes segment i's total assets, M_i the total-capital-to-assets multiple for the median single-segment firm in segment i's industry, EV the firm's excess value, V the firm's total capital (market value of common equity plus book value of debt), and n the total number of business segments. Following BO, I cut off extreme values above $+1.386$ and below -1.386.

Given that multiple-valuation commonly relies on peer groups for the derivation of benchmark multiples, firm specific characteristics oftentimes are overlooked. This is especially true for asset multiple valuation, ignoring a firm's operating profitability, investment behavior and diversification. Systematic differences between firms with low and high dispersion in analyst estimates in any of these variables might drive the relation between excess value and analyst dispersion reported later on. In order to control for such effects, I use a second measure of excess value

$$\mathrm{EV}_2 = \varepsilon \tag{4}$$

computed as the residual of the following linear regression model, accounting for year and firm fixed-effects:

$$\mathrm{EV}_1 = \alpha + \beta_1 \mathrm{MULTI} + \beta_2 \mathrm{SIZE} + \beta_3 \mathrm{INCOME} + \beta_4 \mathrm{CAPSPEND} + \beta_5 \mathrm{HERF} + \varepsilon. \quad (5)$$

The regression model includes the standard variables profitability measured as net income divided by total sales (INCOME), capital expenditures relative to total sales (CAPSPEND), as well as a dummy variable identifying multi-segment firms (MULTI), amongst others used by BO and Lins and Servaes (1999). In contrast to their study, I use the percentile rank of the CRSP market value of equity instead of the log of total assets as a proxy for firm size (SIZE). More specifically, I define (SIZE) as

$$\mathrm{EV}_1 = \frac{Rank(\mathrm{SHRPRC} * \mathrm{NOSH})}{\mathrm{N}}, \quad (6)$$

where SHRPRC refers to the shareprice and NOSH to the number of shares as reported in the monthly CRSP dataset. N is the number of observations included in the regression. The justification for this deviation from the standard BO regression model is twofold. First, the market value of equity has been identified as common factor explaining a part of the variation in the cross-section of returns by Fama and French (1993) and is used in numerous studies including the one by DMS for sorting the stocks in the cross section. Second, the high skewness of both size variables - even if logarithmic - induces heteroscedasticity and biases regression results. Using any of the two size variables without percentile rank transformation turns out to eliminate only a fraction of the cross-sectional variation in excess values between size quintiles. In addition to the basic regression model, I include the Herfindahl Index HERF computed based on the segments' market values in order to control more accurately for the value effects of corporate diversification.

Consistent with previous literature, I observe positive relationships between EV and SIZE, INCOME, as well as CAPSPEND, and a negative relationship between EV and LEVER as well as the dummy variable MULTI. All relationships are statistically significant at the 1% level.

4.2 Empirical Results

Again, I assign all stocks included in the sample to 25 portfolios based on market capitalization and analyst dispersion quintiles of the previous month. Instead of looking at stock returns, I then compute the average credit rating, as well as the average excess value for every portfolio. Table 2 and Table 3 display the results.

[Table 2 about here.]

[Table 3 about here.]

Two effects are clearly observable. First, higher analyst dispersion goes along with low credit quality. For four of five size quintiles, as well as across the entire sample, the difference in credit ratings between the first and fifth dispersion quintile is significant at the one percent level. This supports the hypothesis that firms with higher uncertainty about their cash-flow streams face a higher cost of external bank financing. [5]. Second, higher uncertainty implies lower equity values. For all five size quintiles and across the entire sample the difference in both measures of excess values between the first and fifth dispersion quintile is significant at the one percent level. Abnormal stock returns observed for high-dispersion stocks do not imply high stock valuations.

[5] Whether or not the entire cost of capital increases despite the abnormally low stock returns reported previously, is not investigated in this study.

Academics and managers alike are warned against assigning positive value effects to increases in uncertainty or information asymmetry.

5 Conclusion

Recent studies by Diether et al. (2002) and Johnson (2004) provide evidence of a negative relation between dispersion in analyst forecasts and stock returns, being particularly pronounced for the levered firm. Both suggest that their findings indicate a positive impact of dispersion in analyst estimates on shareholder value, offering different explanations. This study complements their work by analyzing the relationship between information uncertainty measured by analyst dispersion and coverage on the one hand and simple measures of excess value based on multiple valuation on the other. In contrast to previous reasoning, a negative relation between analyst dispersion on the one hand and credit quality as well as excess value on the other hand is found. The aggregate evidence indicates that intransparency decreases shareholder value, possibly due to intensified agency problems. On a more general level, results shed light on the relation between return and shareholder value and caution academics to interpret low stock returns as evidence for highly-priced securities.

The results of DMS and Johnson (2004), taken together with the evidence provided in this paper, thus require additional investigation. One such explanation might be rooted in agency conflicts between shareholders and management. Independent of whether uncertainty about firm risk and value is induced by management itself, it might allow management to more flexibly pursue their own interests without being penalized by shareholders. For example, uncertainty enables management to disguise shareholders about the true risk or value of projects taken. Intransparency can thus intensify agency conflicts stemming from management's risk aversion (job protection) and tendency to overinvest (empire building). Those agency conflicts can result in observable and unobservable agency costs. Observable agency costs include lower operative and investment efficiency and can (at least to some extent) be inferred from accounting data. For my sample, less transparent firms tend to have lower rates of asset utilization and higher expense ratios. Shareholders, being able to infer these agency costs, impose a discount on the intransparent firm, consistent with the evidence provided in this paper. Unobservable agency costs to shareholders can stem from risk reductions in the levered firm, as these are generally not inferable from accounting data. In order to secure their positions, managers have the incentive to reduce firm risk. Due to increased default risk, this incentive is intensified in the levered firm in which "reverse asset substitution" can lead to a transfer of wealth from share- to bondholders. In order not to punished by shareholders or even be forced into riskier projects, managers have a disincentive to reveal information on the firm's riskiness to both, debt and shareholders - assuming that information about low firm risk conveyed to debt holders would also reach shareholders sooner or later. Debtholders are conservative and price the uncertainty, resulting in more expensive debt for the intransparent firm. Partly in line with the argumentation of DMS shareholders on the other hand may be optimistic, also assuming the firm to be riskier than it actually is. They therefore overprice equity as a call option and do not obtain the future returns they expected. This view is in line with the findings of DMS, Johnson (2004) and the evidence provided in this paper. However, it strongly rejects the view that intransparency leads to an increase in shareholder value. Rather, it is line with Kelly and Ljungqvist (2007) and others, arguing that transparency creates shareholder value. In order to further investigate this potential line of reasoning, future research might look at the connection between executive compensation and asset pricing anomalies.

References

Berger, P. G., Ofek, E., 1995. Diversification's effect on firm value. Journal of Financial Economics 37 (1), 39–65.

Diether, K. B., Malloy, C. J., Scherbina, A., 2002. Differences of opinion and the cross section of stock returns. Journal of Finance 57 (5), 2113–2141.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33 (1), 3–56.

Jarrow, R., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. Journal of Finance 56 (2), 699–720.

Johnson, T. C., 2004. Forecast dispersion and the cross section of expected returns. Journal of Finance 59 (5), 1957–1978.

Kelly, B., Ljungqvist, A., 2007. The value of research. NYU Stern School of Business, Working Paper 10 (1), 1–45.

Lins, K., Servaes, H., 1999. International evidence on the value of corporate diversification. Journal of Finance 54 (6), 2215–2239.

Miller, E. M., 1977. Risk, uncertainty and divergence of opinion. Journal of Finance 32 (4), 1151–1168.

List of Tables

Table 1
Average Portfolio Returns by Ex-Ante Size and Analyst Dispersion: Each month, stocks are assigned to 25 portfolios based on the quintile of their market-capitalization and the quintile of their analyst dispersion of the previous month. Analyst dispersion DISP is defined as the standard deviation of analysts‘ prediction of firm i‘s earnings per share in the next year (EPS1), divided by the mean analyst forecast for that firm. The table reports the average of 263 monthly stock returns from February 1984 until December 2005.

	Small				Large	All
	S1	S2	S3	S4	S5	
D1	0.014	0.013	0.010	0.011	0.010	0.012
D2	0.012	0.010	0.010	0.010	0.010	0.011
D3	0.008	0.010	0.010	0.010	0.009	0.009
D4	0.005	0.008	0.008	0.008	0.011	0.008
D5	0.002	0.007	0.006	0.007	0.010	0.007
D5-D1	-0.012^*	-0.006^*	-0.004^*	-0.003	-0.001	-0.005

$'*'$ indicates significance at the 1% Level. Differences of short-D1-long-D5 trading strategies' stock returns from zero are tested for all size quintiles using t-tests.

Table 2
Average Credit Rating by Ex-Ante Analyst Dispersion and Size: Each month, stocks are assigned to 25 portfolios based on the quintile of their market-capitalization and the quintile of their analyst dispersion of the previous month. Analyst dispersion DISP is defined as the standard deviation of analysts‘ prediction of firm i‘s earnings per share in the next year (EPS1), divided by the mean analyst forecast for that firm. The table reports the average of 263 monthly S&P long-term issuer credit ratings from February 1984 until December 2005 as reported in Compustat. Low numbers reflect a low credit risk, high numbers a high credit risk.

	Small				Large	All
	S1	S2	S3	S4	S5	
D1	14.675	13.405	11.868	10.382	7.719	11.610
D2	14.752	13.513	11.812	10.373	8.234	11.737
D3	14.689	13.624	12.145	10.636	8.688	11.956
D4	14.927	13.977	12.694	11.315	9.343	12.451
D5	15.214	14.675	13.715	12.356	10.330	13.258
D5-D1	0.539	1.270*	1.847*	1.974*	2.611*	1.648

′*′ indicates significance at the 1% Level. Differences of short-D1-long-D5 trading strategies' credit rating from zero are tested for all size quintiles using t-tests.

Table 3

Average Excess Values by Ex-Ante Analyst Dispersion and Size: Each month, stocks are assigned to 25 portfolios based on the quintile of their market-capitalization and the quintile of their analyst dispersion of the previous month. Analyst dispersion DISP is defined as the standard deviation of analysts‘ prediction of firm i‘s earnings per share in the next year (EPS1), divided by the mean analyst forecast for that firm. Panel (a) reports the average of 263 monthly excess values from February 1984 until December 2005 computed using segment based asset-multiple valuation following Berger and Ofek (1995). Low numbers reflect a low stock valuate relative to industry peers. Panel (b) reports results for an extended measure of excess value, adjusted for firm-specific characteristics – including operating profitability, investment behavior and level of diversification – using a fixed effects regression model.

(a) Average Excess Value EV_1

	Small				Large	All
	S1	S2	S3	S4	S5	
D1	0.062	0.181	0.263	0.271	0.313	0.218
D2	0.019	0.153	0.195	0.194	0.230	0.158
D3	−0.040	0.088	0.134	0.126	0.188	0.099
D4	−0.089	0.043	0.084	0.076	0.131	0.049
D5	−0.163	−0.032	0.016	0.025	0.092	-0.013
D5-D1	−0.226*	−0.213*	−0.247*	−0.246*	−0.222*	-0.231

(b) Average Excess Value EV_2

	Small				Large	All
	S1	S2	S3	S4	S5	
D1	0.034	0.080	0.106	0.060	0.036	0.063
D2	0.003	0.062	0.064	0.012	0.004	0.029
D3	−0.031	0.021	0.025	−0.029	−0.022	-0.007
D4	−0.054	0.006	−0.004	−0.066	−0.055	-0.035
D5	−0.088	−0.016	−0.029	−0.070	−0.082	-0.057
D5-D1	−0.122*	−0.095*	−0.136*	−0.130*	−0.117*	-0.120

'*' indicates significance at the 1% Level. Differences of short-D1-long-D5 trading strategies' excess values from zero are tested for all size quintiles using t-tests.