UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Master Degree Project in Finance

Analyst Disagreement- A Recipe for Disaster: The Cross-section of Scandinavian Stock Returns

Victor Svärd and Robert Wigermo

Supervisor: Hans Jeppsson
Master Degree Project No. 2015:96
Graduate School

Analyst Disagreement- A Recipe for Disaster:
The Cross-Section of Scandinavian Stock Returns

ROBERT WIGERMO and VICTOR SVÄRD*

ABSTRACT

We show that dispersion in analysts' earnings forecasts is negatively related to future returns on the Scandinavian stock markets. This negative relation is most pronounced for small stocks. Considering dispersion in analysts' earnings forecasts as a proxy for differences of opinion, the results support the view that differences of opinion in the presence of short sale constraints lead to overvaluation. The results cannot be explained by other known factors and they are robust to various changes in methodology. The results suggest that traders can use dispersion in analysts' earnings forecasts as a profitable trading rule on the Scandinavian stock markets.

JEL Classification: G12; G14; G15

Keywords: Differences of opinion, Short sale constraints, Return predictability

* The authors Robert Wigermo 860801 and Victor Svärd 890626 thank Hans Jeppsson for supervising this thesis.

Introduction

This thesis shows that stocks with high dispersion in analysts' earnings forecasts earn significantly lower returns than stocks with low dispersion in analysts' earnings forecasts on the Scandinavian stock markets. This negative relation between dispersion in analysts' earnings forecasts and future returns is most pronounced for small stocks. In fact, the average return differential between large stocks with low dispersion in analysts' earnings forecasts and small stocks with high dispersion in analysts' earnings forecast is 16.2% per year.

We focus on two firm characteristics- differences of opinion and short sale constraints. The idea that these characteristics might affect future returns goes back to Miller (1977). Miller argues that, in the presence of short sale constraints, differences of opinion may lead to overvaluation since pessimists want to hold a negative quantity, but are constrained to hold zero shares. Therefore, as long as optimists can absorb the outstanding shares, the price will be higher than that of the average opinion. Miller also argues that, the more divergent the opinions among investors, the more pronounced the overvaluation.

We follow the notion in Miller (1977) that any type of market friction, which prevents traders with pessimistic opinions from selling short, will produce a negative relation between differences of opinion and future returns. Indeed, such frictions exist. First, not all stocks can be shorted. For stocks that can be shorted, there are direct costs associated with the sale- the lender charges the investor a lending fee. Second, there are indirect costs associated with a short sale. The proceeds of a short sale remain with the lender as collateral (often more than 100%) and the lender can demand the stock back at any time. The fact that the proceeds of a short sale stay with the lender has serious implications. A short sale is only profitable when the total return on the stock is less than "the rebate" (the interest on the collateral minus the lending fee). Even if an investor short sells a stock with a subnormal return, he or she will lose money as long as the return is above "the rebate". Thus, short sales can only dampen overvaluation, not eliminate it.

The Miller (1977) argument has been tested on U.S data. The papers closest to ours are Diether, Malloy and Scherbina (2002), Lee and Swaminathan (2000) and Boehme, Danielsen and Sorescu (2006). Diether et al. (2002) use dispersion in analysts' earnings forecasts as a proxy for differences of opinion. They show that dispersion in analysts' earnings forecasts is negatively related to future returns over the time period 1983 to 2000. Lee and Swaminathan (2000) consider trading volume as a proxy for differences of opinion and get similar results. They show that trading volume is negatively related to future returns over the time period

1965 to 1995. Boehme et al. (2006) take it a step further and consider the interaction between differences of opinion and short sale constraints. They use dispersion in analysts' earnings forecasts and trading volume as proxies for differences of opinion and lending fees, short interest and traded options as proxies for short sale constraints. They find that stocks are substantially overvalued when they are subject to both conditions simultaneously.

But, even though dispersion in analysts' earnings forecasts has been negatively related to future returns in the past, it may not be true in today's capital markets. The subsample analysis in Diether et al. (2002) shows that much of the negative relation between dispersion in analysts' earnings forecasts and future returns disappears in the post-1992 period. They suggest decreasing short sale costs and more transparent companies (less investor uncertainty) as possible reasons. Indeed, the dispersion in analysts' earnings forecasts decreases over time in their sample.

We test the Miller (1977) argument for the post-1992 period on the Scandinavian stock markets. Following Diether et al. (2002), we use dispersion in analysts' earnings forecasts as a proxy for differences of opinion. We consider the interaction between differences of opinion and short sale constraints by using large stocks as a proxy for low short sale constraints and small stocks as a proxy for high short sale constraints. There are several reasons for using size as a proxy for short sale constraints. First, D´Avolio (2002) gets access to data from a large lending intermediary and finds that lending fees decrease with size. The data also show that many small stocks cannot be shorted and that some small stocks are never shorted even when it is possible. Second, the fraction of institutional ownership increases with size (Nagel, 2005). Since institutional investors are the main lenders (D´Avolio, 2002) - the higher the fraction of institutional ownership, the higher the loan supply, and the lower the short sale constraints. Third, large stocks are more likely to have traded options. Options relax short sale constraints since it allows traders to take short positions synthetically when they cannot short sell directly (see Danielsen and Sorescu (2001) for empirical evidence and a discussion why options relax short sale constraints). Thus, our proxy (size) incorporates all common measures for short sale constraints.

The Scandinavian stock markets are of particular interest since they have a different institutional setting than the U.S stock markets. Saffi and Sigurdsson (2011) show that Scandinavian stocks have higher average lending fees than U.S stocks. Higher lending fees (higher short sale constraints) suggest that the negative relation between dispersion in analysts' earnings forecasts and future returns may be more pronounced on the Scandinavian stock markets.

The thesis contributes to the literature in three ways. First, since most studies of the Miller (1977) argument are based on the same NYSE, Amex, Nasdaq sample, the studies cannot be interpreted as independent results. We run an out of sample test of the Miller (1977) argument and show that the negative relation between dispersion in analysts' earnings forecasts and future returns is even more pronounced on the Scandinavian stock markets. Second, we use the monotonic relation (MR) test developed by Patton and Timmermann (2010) to test if the relation between dispersion in analysts' earnings forecasts and future returns is monotonically decreasing. The MR test allows us to test the relation between dispersion in analysts' earnings forecasts and future returns across all levels of dispersion. Earlier studies only make use of the return differential between the two extreme portfolios. Third, we consider size as a proxy for short sale constraints.

The thesis is organized as follows. Section I presents two competing hypotheses about the relation between dispersion in analysts' earnings forecasts and future returns. Section II shows data and sample characteristics. In Section III, we form test portfolios and show that dispersion in analysts' earnings forecasts is negatively related to future returns. We also show that this negative relation is most pronounced for stocks with high short sale constraints (small stocks). In Section IV, we run time series regressions and show that the negative relation between dispersion in analysts' earnings forecasts and future returns cannot be explained by exposures to beta, size, book to market or momentum. Section V shows that the results are robust to various changes in methodology. In Section VI, we conclude and give implications for traders and regulators.

I. Hypotheses

We have two competing hypotheses about the relation between dispersion in analysts' earnings forecasts and future returns. The first hypothesis (H_0) builds on the subperiod analysis in Diether et al. (2002) and the view that the negative relation between dispersion in analysts' earnings forecasts and future returns disappears over time due to decreasing short sale costs and less investor uncertainty. This hypothesis is also consistent with the predictions in Diamond and Verrecchia (1987). In their model, a rational market maker (with perfect information) sets bid and ask prices in a market where some investors with pessimistic opinions are constrained from selling short. Their model predicts no overvaluation.

H_0: *There is no relation between dispersion in analysts' earnings forecasts and future returns in today's capital markets.*

The second hypothesis (H_1) builds on the Miller (1977) argument that differences of opinion in the presence of short sale constraints lead to overvaluation. Miller argues that, the more divergent the opinions among investors, the more pronounced the overvaluation.

H_1: *There is a negative relation between dispersion in analysts' earnings forecasts and future returns.*

We test H_1 for small, medium and large stocks as well as for the entire sample. The Miller (1977) argument implies that the negative relation between dispersion in analysts' earnings forecasts and future returns should be most pronounced for small stocks (for which the short sale constraints are most likely to bind). In contrast, the negative relation between dispersion in analysts' earnings forecast and future returns should be weakest for large stocks (for which the short sale constraints are least likely to bind).

II. Data and Sample Characteristics

The sample consists of 667 non-financial firms from the Stockholm, Oslo and Copenhagen Stock Exchange.[1] We exclude financial firms since they are subject to different risk factors and accounting standards (Viale, Kolari and Fraser, 2009). Excluding financial firms are standard in asset pricing tests and increase the comparability of our results.

We obtain the data from Thomson Reuters Datastream (TRD) and it consists of both active and "dead" firms.[2] Active firms are exchange listed today. "Dead" firms have been exchange listed during our sample period, but have ceased to exist (due to takeovers, mergers, defaults or other reasons). Combining these makes our sample free from potential issues related to survivorship bias.

For firms that have issued different types of securities (e.g. "voting" and "non-voting" shares), we chose the security with the highest level of analysts' coverage. We exclude preferred stocks and other non common equity securities.

The analysts' earnings forecasts are one-year net income forecasts and obtained from the Institutional Brokers Estimate System (I/B/E/S) on TRD.[3] Following Diether et al. (2002), we define dispersion in analysts' earnings forecasts as the standard deviation of the earnings

[1] We use the Industry Classification Benchmark (ICB) for defining financial stocks. Financial stocks consist of Banks, Insurance, Real Estate and Financial services.

[2] We use the following all share TRD time series: OMX Stockholm (SWSEALI), Oslo Exchange All Share (OSLOASH), OMX Copenhagen (COSEASH), OMX Stockholm "dead series" (DEADSD), Oslo Exchange "dead series" (DEADNW) and the OMX Copenhagen "dead series" (DEADDK).

[3] I/B/E/S do not reveal where the individual forecasts come from but they state that "international companies (i.e. non-US companies) are covered by international (non-US) analysts."

forecasts divided by the absolute value of the mean of the same forecasts. But, in contrast to Diether et al. (2002), we use net income forecasts instead of earnings per share (EPS) forecasts. As noted in Diether et al. (2002), the EPS forecast data from I/B/E/S is subject to rounding errors from historical stock splits.[4] We use net income forecasts to avoid potential issues with these rounding errors.

We use monthly data from January 1996 to March 2015. We start in January 1996 since prior to this date there are not enough firms for the tests performed in this thesis. The data is obtained the 27th each month and all variables are measured in SEK.

We exclude firms with a stock price of less than 10 SEK or a market value below 150 million SEK. We exclude these stocks to ensure that the results are not driven by small, hardly investable stocks or by bid-ask bounce. Indeed, Conrad and Kaul (1993) show that much of the long term mean reversion "anomaly" documented in De Bondt and Thaler (1985) disappear when excluding illiquid, low priced stocks. Since we measure *dispersion* in analysts' earnings forecasts, each firm must also be covered by two or more analysts.

In each month τ, included firms need total return data between τ-2 and τ-12. This requirement ensures that we use the same number of observations in the test portfolios in Section III as when creating the momentum portfolios in Section IV. Following Fama and French (1993) we also exclude firms with negative book equity from the sample.

The number of firms varies over time. For example, a micro cap firm might be excluded in the beginning of the sample period, but later included due to an increase in market value. Similarly, a firm might be covered by two or more analysts only temporarily and will therefore be included only during that period of time.

Table I shows sample characteristics. Panel A shows the average number of firms over the sample period. The number of firms increases over time until the financial crisis in 2008 after which the number of firms decreases considerably.

Panel B shows that the Stockholm stock exchange is the largest constituent in the sample. Together with the Oslo stock exchange they account for more than 80% of the firms. There are around as many "dead" as active firms in the sample. But, the active firms have a better coverage with about three times as many observations.

We calculate discrete monthly returns from a total return index for each stock. The total return index shows a theoretical growth in value assuming that dividends are reinvested in the

[4] Diether et al. (2002) get access to unadjusted EPS forecasts and thus avoid potential issues with the rounding error.

stock at the closing price on the ex dividend date.[5] As in Fama and French (1993), we measure firm size by its market value (common shares outstanding times stock price). The stock price is the official closing price adjusted for stock splits. Following Fama and French (1993), we define book equity (BE) as the book value of common equity plus deferred taxes (if available) minus the book value of preferred stocks (if available). We show all variables with its corresponding TRD code in the Appendix.

Table I

Sample Characteristics

Panel A shows the average number of firms for different subperiods. All firms have been traded on the Stockholm, Oslo or Copenhagen Stock Exchange. Panel B shows the number of firms and observations from each stock exchange. Active firms are exchange listed today. "Dead" firms have been exchange listed during our sample period, but have ceased to exist. Each firm is covered by two or more analysts, has a stock price of at least 10 SEK and a market value of 150 million SEK or more. Financial firms and firms with negative book equity are excluded.

Panel A

Time Period	Average number of firms
1996- 1999	168
2000- 2003	194
2004- 2007	218
2008- 2011	247
2012- 2015	169

Panel B

	Active			"Dead"		
	Stockholm	Oslo	Copenhagen	Stockholm	Oslo	Copenhagen
Number of firms	166	108	64	131	148	50
Number of observations	16 477	9 302	7 987	5 973	5 774	2 339

Table II shows summary statistics and cross-correlations. Panel A shows that the median number of analysts' earnings forecasts is five and at least 30% of the observations have two or three analysts' earnings forecasts. The mean dispersion in analysts' earnings forecasts is well above the 70% percentile since some firms have very high levels of dispersion. Similarly, the mean size is well above the 70% percentile since there are some very large firms in the sample.

[5] In TRD, the total return indices are rounded to the nearest cent. As noted in Ince and Porter (2006), for total return indices with values close to zero, this rounding error gets severe. Accordingly, we exclude all observations with a total return index below 1 SEK.

Small cap, mid cap and large cap each represents around one third of the sample.[6] Panel B shows that the correlation between the variables is low except between size and the number of analysts' earnings forecasts (correlation coefficient of 0.56).

Table II

Summary Statistics and Cross-Correlations

Panel A shows summary statistics and Panel B shows cross-correlations. The Nr of Forecasts is the number of one-year net income analysts' forecasts. The forecasts are obtained from the Institutional Brokers Estimate System (I/B/E/S). Dispersion is the dispersion in analysts' earnings forecasts and is defined as the standard deviation of the net income forecasts divided by the absolute value of the mean of the same forecasts. Size is the market value (common shares outstanding times stock price). BE/MV is the book equity divided by the market value. Book equity (BE) is defined as the book value of common equity plus deferred taxes (if available) minus the book value of preferred stocks (if available).

Panel A				
	Mean	Median	30th percentile	70th percentile
Nr of Forecasts	7	5	3	8
Dispersion (%)	51	13	8	23
Size (billion SEK)	21.8	3.8	1.7	9.9
BE/MV	0.64	0.49	0.33	0.72

Panel B				
	Dispersion	Nr of Forecast	Size	BE/MV
Dispersion				
Nr of Forecasts	-0.02			
Size	-0.01	0.56		
BE/MV	0.03	-0.07	-0.11	

III. Dispersion in Analysts' Earnings Forecasts and Returns

To evaluate the relation between dispersion in analysts' earnings forecasts and future returns we use a methodology similar to the one in Jegadeesh and Titman (1993). In each month τ, we form five portfolios (with an equal number of stocks) based on the level of dispersion in analysts' earnings forecasts as of the previous month τ-1. The one month lag ensures that all forecasts from τ-1 are available to the public at time τ. Assigning stocks into portfolios diversify away the idiosyncratic part of the returns and thereby reducing the

[6] The Nasdaq OMX Nordic classification system defines large cap as firms with a market value over 1 billion euro, mid cap as firms with a market value between 150 million and 1 billion euro and small cap as firms with a market value below 150 million euro.

estimation errors (see Black, Jensen and Scholes (1972)). The stocks are then held for one month and equally weighted portfolio returns are calculated from τ to $\tau+1$. After calculating portfolio returns for all τ we end up with five return series; one for each portfolio. Each portfolio can be thought of as a “style portfolio” in which its components change over time but its trading rule stays the same.

Table III shows the average monthly returns. The return differential between low dispersion stocks (D1) and high dispersion stocks (D5) is 0.82% and statistically significant at the 5% level. The return differential can be thought of as the return on a zero-cost portfolio with a long position in D1 and a short position in D5. We also use the monotonic relation (MR) test by Patton and Timmermann (2010) to test the relation between dispersion and future returns across all levels of dispersion, not only between the two extreme portfolios. We test the null hypothesis (of the MR test) that the returns are flat across the five portfolios against the alternative hypothesis that the returns are monotonically decreasing. We reject the null hypothesis of a flat relation with a *p*-value of 0.012.

Table III

Mean Portfolio Returns Sorted by Dispersion in Analysts’ Earnings Forecasts

The table shows equally weighted average monthly returns for five portfolios (with an equal number of stocks) which each month are formed based on the level of dispersion in analysts’ earnings forecasts as of the previous month τ-1. The dispersion in analysts’ earnings forecasts is defined as the standard deviation of net income forecasts divided by the absolute value of the mean of the same forecasts. Each firm is covered by two or more analysts, has a stock price of at least 10 SEK and a market value of 150 million SEK or more. Financial firms and firms with negative book equity are excluded. The time period is from January 1996 to March 2015 and all firms have been traded on the Stockholm, Oslo or Copenhagen Stock Exchange during this time. The number of observations is 229. The *t*-statistic in parenthesis is based on Newey-West standard errors. In the *MR*-test, we test the null hypothesis that the returns are flat across the five portfolios against the alternative hypothesis that the returns are monotonically decreasing.

	Mean Returns					
	Dispersion Quintiles					
	Low				High	
	D1	D2	D3	D4	D5	D1-D5
Mean Return (%)	1.20	1.15	0.94	0.75	0.38	0.82**
t-statistic						(2.39)
*MR-test(p-value)=0.012***						

*** p<0.01, ** p<0.05, * p<0.1

The negative relation between dispersion in analysts’ earnings forecasts and future returns supports the Miller (1977) argument. But, we want to see if we can find an even stronger negative relation for stocks with high short sale constraints (small stocks). Indeed, when there are large differences of opinion, but no short sale constraints, both optimists and pessimists will trade, and no overvaluation should exist.

In each month τ we divide the sample into three groups based on size (with an equal number of stocks). We then divide each group into four portfolios (with an equal number of stocks) based on dispersion in analysts' earnings forecasts as of the previous month τ-*1*. After calculating equally weighted portfolio returns for all τ we end up with twelve return series. According to the Miller (1977) argument, the portfolio with large stocks (low short sale constraints) and a low level of dispersion in analysts' earnings forecasts, denoted S3D1, should perform best. In contrast, the portfolio with small stocks (high short sale constraints) and a high level of dispersion in analysts' earnings forecasts, denoted S1D4, should perform worst.

Table IV shows the average monthly portfolio returns sorted by size and dispersion in analysts' earnings forecasts. By considering the interaction between size and dispersion we get higher return differentials between low and high dispersion stocks. The monthly return on the S3D1-S1D4 portfolio is 1.35% and statistically significant at the 1% level. The return on the S1D4 portfolio is even negative (-0.16%).

In line with the Miller (1977) argument, the relation between dispersion in analysts' earnings forecasts and future returns is most pronounced for small stocks (for which the short sale constraints are most likely to bind). The return on the D1-D4 portfolio for small stocks is 1.11% and statistically significant at the 1% level. For medium sized stocks the return on the D1-D4 portfolio is 0.8% and statistically significant at the 5% level. For large stocks (for which the short sale constraints are least likely to bind), the relation between dispersion in analysts' earnings forecasts and future returns is statistically insignificant. We also test the null hypothesis (of the MR test) that the returns are flat across the four portfolios (in each size group) against the alternative hypothesis that the returns are monotonically decreasing. For small and medium sized stocks, we reject the null hypothesis of a flat relation with a *p*-value of 0.009 and 0.006 respectively. For large stocks we cannot reject the null hypothesis of a flat relation with a *p*-value of 0.293.

Table IV

Mean Portfolio Returns Sorted by Size and Dispersion in Analysts' Earnings Forecasts

The table shows equally weighted average monthly returns for twelve portfolios. In each month τ we divide the sample into three groups based on size (with an equal number of stocks). We then divide each group into four portfolios (with an equal number of stocks) based on dispersion in analysts' earnings forecasts as of the previous month τ-1. The dispersion in analysts' earnings forecasts is defined as the standard deviation of net income forecasts divided by the absolute value of the mean of the same forecasts. Each firm is covered by two or more analysts, has a stock price of at least 10 SEK and a market value of 150 million SEK or more. Financial firms and firms with negative book equity are excluded. The time period is from January 1996 to March 2015 and all firms have been traded on the Stockholm, Oslo or Copenhagen Stock Exchange during this time. The number of observations is 229. The *t*-statistics in parentheses are based on Newey-West standard errors. In the *MR*-test, we test the null hypothesis that the returns are flat across the four portfolios against the alternative hypothesis that the returns are monotonically decreasing.

Mean Returns (%)			
	Size (S)		
	Small		Large
Dispersion (D)	S1	S2	S3
D1 (low)	0.95	1.39	1.19
D2	0.55	1.18	1.14
D3	0.47	1.07	1.24
D4 (high)	-0.16	0.59	0.97
D1-D4	1.11***	0.8**	0.22
t-statistic	(3.62)	(2.44)	(0.65)
MR-test (p-value)	0.009***	0.006***	0.293
S3D1-S1D4		1.35***	
t-statistic		(3.03)	

*** p<0.01, ** p<0.05, * p<0.1

IV. Regression Analysis

To ensure that the return differentials between high and low dispersion stocks are not due to other known factors we perform time series regressions. Fama and French (1996) show that their three-factor model can explain many of the early CAPM "anomalies". Similarly, Carhart (1997) finds that his four-factor model can explain early evidence of persistence within the mutual fund industry. Thus, we use the Fama French (1993) three-factor model and the Carhart (1997) four-factor model to see if they can explain the returns from Section III.

For the Fama French three-factor model we run the following time-series regression.

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i[SMB_t] + h_i[HML_t] + \varepsilon_{it} \qquad (1)$$

$R_i - R_f$ is the excess return on the test portfolios from Section III. $R_m - R_f$ is the excess return on our proxy for the market portfolio. We construct a value-weighted total return index from all included stocks in our sample as a proxy for the market portfolio. We use the Swedish one month Treasury-bill rate as the risk-free rate. In addition to the market factor, Fama and French add a size (SMB) factor and a book to market (HML) factor.[7] We follow the procedure in Fama and French (1993) when creating these factors. In each month τ, we form two (with an equal number of firms) groups based on size, denoted small and big. We also form three groups (the breakpoints are the 30th and 70th percentiles) based on BE/MV as of τ-6, denoted value, neutral and growth. Value represents high BE/MV; growth represents low BE/MV. The six month lag ensures that the financial statement data is available to the public at the time of the portfolio formation, τ. The intersections between the two groups formed on size and the three groups formed on BE/MV represent six portfolios: Small Value (SV), Small Neutral (SN), Small Growth (SG), Big Value (BV), Big Neutral (BN) and Big Growth (BG). For example, for a firm to be included in the SV portfolio, it needs to be included in both the small and the value group.

The SMB factor is the value-weighted return on a portfolio with small stocks less the value-weighted return on a portfolio with large stocks:

$$SMB = \frac{1}{3}(SV + SN + SG) - \frac{1}{3}(BV + BN + BG) \quad (2)$$

The HML factor is the value-weighted return on a portfolio with high BE/MV less the value-weighted return on a portfolio with low BE/MV:

$$HML = \frac{1}{2}(SV + BV) - \frac{1}{2}(SG + BG) \quad (3)$$

For the Carhart four-factor model we run the following time series regression.

$$R_{it} - R_{ft} = \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + s_i[SMB_t] + h_i[HML_t] + m_i[WML_t] + \varepsilon_{it} \quad (4)$$

Carhart adds a momentum factor (WML) to the three-factor model.[8] We follow the procedure in Carhart (1997) when creating the WML factor. In each month τ, we form two (with an equal number of firms) groups based on size, denoted small and big. We also form three groups (the breakpoints are the 30th and 70th percentiles) based on returns from τ-12 to

[7] The finding that size affects returns goes back to Banz (1981). He finds that small (large) stocks earn a higher (lower) return than predicted by the CAPM. The book to market effect was first documented in Stattman (1980). He finds a positive relation between book to market and future returns.

[8] The finding that momentum affects returns goes back to Jegadeesh and Titman (1993).

τ-2, denoted winner, neutral and loser.[9] The intersections between the two groups formed on size and the three groups formed on past returns represent six portfolios: Small Winner (SW), Small Neutral (SN), Small Loser (SL), Big Winner (BW), Big Neutral (BN) and Big Loser (BL).

The WML factor is the value-weighted return on a portfolio with high returns from τ-12 to τ-2 less the value-weighted return on a portfolio with low returns from τ-12 to τ-2:

$$WML = \frac{1}{2}(SW + BW) - \frac{1}{2}(SL + BL) \tag{5}$$

Table V shows descriptive statistics about the four factors. Panel A shows the monthly mean returns for the four factors. The historical risk premium has been high, with an annual excess return of 9.72%. There is a strong momentum effect (12.84% per year) while no evidence of a size or book to market effect. Panel B shows the cross-correlation for the factors. The low correlation between factors supports the notion that they represent different risk factors.

Table V

Mean Returns and Cross-Correlations for Factors

Panel A shows monthly mean returns for four factors on the Scandinavian stock exchanges between January 1996 and March 2015. The number of observations is 229. $R_m - R_f$ is the excess return on our proxy for the market portfolio. The risk-free rate is the Swedish one month Treasury-bill rate. SMB is the value-weighted return on a portfolio with small stocks less the value-weighted return on a portfolio with large stocks. HML is the value-weighted return on a portfolio with high BE/MV less the value-weighted return on a portfolio with low BE/MV. WML is the value-weighted return on a portfolio with high returns from τ-12 to τ-2 less the value-weighted return on a portfolio with low returns from τ-12 to τ-2. Panel B shows the cross-correlation between the factors. We use the same sample of firms for creating the factors as we use when creating the test portfolios in Section III. The *t*-statistics in parentheses are based on Newey-West standard errors.

Panel A

	$R_m - R_f$	SMB	HML	WML
Mean returns (%)	0.81**	-0.28	0.19	1.07***
t-statistic	(1.97)	(-1.18)	(0.41)	(2.67)

*** p<0.01, ** p<0.05, * p<0.1

Panel B

	SMB	HML	$R_m - R_f$	WML
SMB				
HML	0.05			
$R_m - R_f$	0.14	-0.22		
WML	-0.18	-0.14	-0.29	

[9] The last months return, τ-1, is excluded to avoid the short term reversal effect documented in Jegadeesh (1990).

Table VI shows the regression output for the test portfolios sorted by dispersion in analysts' earnings forecasts. We test α_i against zero to see if the factors can explain the individual portfolio returns. We also use the Gibbons, Ross and Shanken (1989) (GRS) F-test to see if we can reject the null hypothesis that all α_i are jointly equal to zero.

Table VI

Regression Analysis of Portfolios Sorted by Dispersion in Analysts' Earnings Forecasts

This table shows the regression output of the Fama French (1993) three-factor model and the Carhart (1997) four-factor model on the equally weighted portfolio returns sorted by dispersion in analysts' earnings forecasts from Section III.

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i[SMB_t] + h_i[HML_t] + m_i[WML_t] + \varepsilon_{it}$$

In the Fama French three-factor model the WML factor is excluded from the regression. $R_i - R_f$ is the excess return on the test portfolios from Section III. $R_m - R_f$ is the value-weighted excess return on our proxy for the market portfolio. The risk-free rate is the Swedish one month Treasury-bill rate. SMB is the value-weighted return on a portfolio with small stocks less the value-weighted return on a portfolio with large stocks. HML is the value-weighted return on a portfolio with high BE/MV less the value-weighted return on a portfolio with low BE/MV. WML is the value-weighted return on a portfolio with high returns from τ-12 to τ-2 less the value-weighted return on a portfolio with low returns from τ-12 to τ-2. The sample period is January 1996 to March 2015. The number of observations is 229. The *t*-statistics in parentheses are based on Newey-West standard errors. The GRS test statistics are shown in the bottom of the table.

		Risk Factors				Adj. R^2
Portfolio	Alpha (%)	$R_m - R_f$	SMB	HML	WML	(%)
D1 (low)	0.40***	0.80***	0.36***	0.19***		87.02
	(2.74)	(25.33)	(9.41)	(5.17)		
	0.40***	0.80***	0.36***	0.18***	-0.01	86.96
	(2.70)	(23.21)	(9.58)	(5.08)	(-0.20)	
D2	0.29**	0.89***	0.43***	0.21***		87.93
	(2.11)	(24.80)	(7.60)	(6.08)		
	0.30**	0.88***	0.42***	0.20***	-0.02	87.91
	(2.06)	(22.71)	(7.58)	(5.48)	(-0.49)	
D3	0.03	0.95***	0.45***	0.25***		91.29
	(0.20)	(50.52)	(13.43)	(6.91)		
	0.01	0.95***	0.45***	0.25***	0.01	91.26
	(0.11)	(46.55)	(12.73)	(7.21)	(0.38)	
D4	-0.18	1.04***	0.68***	0.30***		90.46
	(-1.57)	(44.25)	(18.36)	(13.16)		
	-0.14	1.03***	0.67***	0.29***	-0.03	90.48
	(-1.20)	(51.31)	(19.80)	(11.12)	(-1.20)	
D5 (high)	-0.58***	1.18***	1.03***	0.36***		89.66
	(-3.27)	(29.35)	(17.48)	(6.51)		
	-0.46**	1.15***	1.00***	0.34***	-0.09	90.02
	(-2.17)	(34.98)	(18.27)	(6.36)	(-1.62)	
GRS 3 Factor = 4.46						
GRS 4 Factor = 3.64						

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The estimated alphas of D1 and D2 are positive and statistically significant at the 1% and 5% level respectively. The alpha of the D1 portfolio is a nontrivial return of 0.4%. The estimated alpha for D5 is -0.46% in the four-factor model and is statistically significant at the 5% level. Low dispersion stocks behave like big, low beta stocks. In contrast, high dispersion stocks behave like small, past losers with a high beta. Moreover, high dispersion stocks load more on HML than low dispersion stocks. We reject the null hypothesis that the factors can explain the average returns on the five portfolios sorted by dispersion in analysts' earnings forecasts (GRS test statistics of 4.46 and 3.64).

Table VII shows the regression output for the zero-cost portfolios (return differentials) from Section III. The D1-D5 portfolio has an estimated alpha of 0.86% in the four-factor model and is statistically significant at the 1% level. The estimated alpha is even higher than the return differential in Section III. It seems like exposures to beta, size, book to market and momentum cannot account for any of the return differential between D1 and D5. The estimated alphas for the S1D1-S1D4, S2D1-S2D4 and S3D1-S3D4 portfolios are also larger than the corresponding return differential in Section III. Small cap (S1D1-S1D4) and mid cap (S2D1-S2D4) have estimated alphas of 1.26% and 0.9% respectively in the four-factor model and they are statistically significant at the 1% level. The estimated alpha for large cap (S3D1-S3D4) is 0.37% in the four-factor model, but as in Section III, statistically insignificant. The S3D1-S1D4 portfolio has an estimated alpha of 1.19% in the four-factor model and is statistically significant at the 1% level.

Controlling for size, BE/MV and momentum is empirically motivated. Whether these factors proxy for fundamental risk factors or whether they are evidence of market inefficiencies are not clear. Nevertheless, we are interested if our test portfolios from Section III can earn higher returns than the returns from passive combinations of the factor portfolios, regardless of whether these factors represent true risk factors or not.

We reject the null hypothesis from Section I that there is no relation between dispersion in analysts' earnings forecasts and future returns in today's capital markets for small and medium stocks as well as for the entire sample. We only fail to reject the null hypothesis for large stocks (for which the short sale constraints are least likely to bind). The results support the Miller (1977) argument that there is a negative relation between dispersion in analysts' earnings forecasts and future returns in the presence of short sale constraints. The regression analysis shows that exposures to beta, size, book to market and momentum cannot account for any of the return differential between low and high dispersion stocks.

Table VII

Regression Analysis of the Zero-Cost Portfolios

This table shows the regression output of the Fama French (1993) three-factor model and the Carhart (1997) four-factor model on the zero-cost portfolios (returns differentials) from Section III. D1-D5 is a zero-cost portfolio with a long position in low dispersion stocks (D1) and a short position in high dispersion stocks (D5). S1D1-S1D4, S2D1-S2D4 and S3D1-S3D4 are zero-cost portfolios with a long position in low dispersion stocks (D1) and a short position in high dispersion stocks (D4) for small cap, mid cap and large cap respectively. S3D1-S1D4 is a zero-cost portfolio with a long position in large stocks with low dispersion and a short position in small stocks with high dispersion.

$$R_{it} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i[SMB_t] + h_i[HML_t] + m_i[WML_t] + \varepsilon_{it}$$

In the Fama French three-factor model the WML factor is excluded from the regression. R_i is the returns on the zero-cost portfolios from Section III. $R_m - R_f$ is the value-weighted excess return on our proxy for the market portfolio. The risk-free rate is the Swedish one month Treasury-bill rate. SMB is the value-weighted return on a portfolio with small stocks less the value-weighted return on a portfolio with large stocks. HML is the value-weighted return on a portfolio with high BE/MV less the value-weighted return on a portfolio with low BE/MV. WML is the value-weighted return on a portfolio with high returns from τ-12 to τ-2 less the value-weighted return on a portfolio with low returns from τ-12 to τ-2. The sample period is January 1996 to March 2015. The number of observations is 229. The *t*-statistics in parentheses are based on Newey-West standard errors.

		Risk Factors				Adj. R^2
Portfolio	Alpha (%)	$R_m - R_f$	SMB	HML	WML	(%)
D1-D5	0.97***	-0.38***	-0.67***	-0.18***		45.47
	(3.69)	(-6.25)	(-8.54)	(-2.89)		
	0.86***	-0.35***	-0.64***	-0.16**	0.09	46.27
	(2.82)	(-6.25)	(-8.78)	(-2.44)	(1.18)	
S1D1-S1D4	1.31***	-0.35***	-0.47***	-0.26***		24.19
	(4.72)	(-4.41)	(-4.54)	(-3.61)		
	1.26***	-0.33***	-0.46***	-0.25***	0.04	24.05
	(3.71)	(-4.79)	(-4.31)	(-3.01)	(0.45)	
S2D1-S2D4	0.96***	-0.35***	-0.52***	-0.10		27.53
	(3.22)	(-5.90)	(-5.02)	(-1.26)		
	0.90***	-0.33***	-0.50***	-0.09	0.07	27.79
	(2.84)	(-5.64)	(-4.86)	(-1.08)	(1.27)	
S3D1-S3D4	0.50*	-0.44***	-0.35***	-0.19***		35.14
	(1.81)	(-9.17)	(-5.21)	(-4.07)		
	0.37	-0.41***	-0.32***	-0.16***	0.10*	36.34
	(1.21)	(-9.56)	(-4.98)	(-3.68)	(1.73)	
S3D1-S1D4	1.34***	-0.34***	-1.16***	-0.21***		47.26
	(3.92)	(-4.49)	(-13.21)	(-3.11)		
	1.19***	-0.31***	-1.12***	-0.18***	0.12	48.02
	(3.06)	(-4.58)	(-13.65)	(-2.62)	(1.38)	

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

V. Robustness Checks

A. Removal of Outliers

To ensure that the results are not driven by a small number of observations with abnormal returns we remove outliers. This robustness check is important when using the TRD database in which extreme returns have been found due to errors in the total return data (Ince and Porter, 2006). Following Artmann et al. (2012) we remove the 0.25% smallest and largest observations from the sample. Table VIII shows the average monthly portfolio returns sorted by dispersion in analysts' earnings forecasts. We see that D1-D5 is 0.96% and statistically significant at the 1% level. This return differential is even higher than in Section III. Thus, the negative relation between dispersion in analysts' earnings forecasts and future returns is not driven by outliers.

B. 3+ Analysts

In this subsection we restrict our sample to firms covered by three or more analysts. The reason is that our proxy for differences of opinion might be less reliable when firms are covered by only two analysts. Table VIII shows that D1-D5 is 0.77% and statistically significant at the 5% level. This return differential is similar to the one in Section III (0.82%). The slightly smaller return differential is probably because the excluded firms are mostly small firms (firm size and analyst coverage are highly correlated) for which the return differential is the highest. Thus, the negative relation between dispersion in analysts' earnings forecasts and future returns is not driven by firms covered by only two analysts.

C. No Lag in Portfolio Formation

In each month τ, we form five portfolios (with an equal number of stocks) based on the level of dispersion in analysts' earnings forecasts as of this month, τ. In this setting the analysts' earnings forecasts are available to investors immediately. Table VIII shows that D1-D5 is 0.78% and statistically significant at the 5% level. This result is close to the results in Section III (0.82%).

It is surprising that the D1-D5 portfolio yields a lower return when we remove the lag. We would expect to get a higher return since, in this setting, the information about dispersion in analysts' earnings forecasts, are more up to date. But, the dispersion in analysts' earnings forecasts is relatively persistent which makes it unlikely that the information about dispersion at month τ-1 is stale at month τ. The persistence in dispersion in analysts' earnings forecasts makes the two strategies similar. Thus, the small difference between the results with and without the lag is probably due to chance.

Table VIII

Robustness Checks: No Outliers, 3+ Analysts and No Lag in Portfolio Formation

This table shows the results from three different robustness checks. In "No Outliers", we remove the 0.25% smallest and largest observations. In "3+ analysts" we exclude all firms covered by only two analysts. In "No Lag" we form portfolios (in each month τ) based on dispersion in analysts' earnings forecasts without a lag. The *t*-statistics in parentheses are based on Newey-West standard errors.

Mean Returns						
	Dispersion Quintiles					
	Low D1	D2	D3	D4	High D5	D1-D5
No Outliers	1.15	1.07	0.91	0.71	0.19	0.96***
t-statistic						(3.06)
3+analysts	1.27	1.10	0.99	0.84	0.50	0.77**
t-statistic						(2.20)
No Lag	1.19	1.16	0.94	0.75	0.41	0.78**
t-statistic						(2.27)

*** p<0.01, ** p<0.05, * p<0.1

D. Different Holding Periods

In this subsection we hold the stocks in each portfolio for 3 and 6 months. In each month τ, we form five portfolios (with an equal number of stocks) based on the level of dispersion in analysts' earnings forecasts as of the previous month τ-1. The stocks are then held for T months (3 or 6) and equally weighted portfolio returns are calculated from τ to τ +T. After calculating portfolio returns for all τ we end up with five return series; one for each portfolio.

Table IX shows the average monthly returns for the 1, 3 and 6 months holding periods. The return differential is 0.59% for the 3 month holding period and 0.47% for the 6 month holding period. The return differentials for both holding periods are statistically significant at the 10% level. We see that the trading rule (buy low dispersion stocks, sell high dispersion stocks) works rather well for longer holding periods as well, even though the return on the D1-D5 portfolio decreases. The reason is the persistence in dispersion in analysts' earnings forecasts. For example, most stocks in the D1 portfolio at time τ satisfy the selection criteria for D1 at time τ +1 as well.

Table IX

Robustness Check- Different Holding Periods

This table shows equally weighted average monthly returns for five portfolios (with an equal number of stocks) which each month are formed based on the level of dispersion in analysts' earnings forecasts as of the previous month τ-1. The stocks are then held for T months (1, 3 or 6) and equally weighted portfolio returns are calculated from τ to τ +T. After calculating portfolio returns for all τ we end up with five return series; one for each portfolio. The dispersion in analysts' earnings forecasts is defined as the standard deviation of net income forecasts divided by the absolute value of the mean of the same forecasts. The *t*-statistics in parentheses are based on Newey-West standard errors.

Mean Returns						
	Dispersion Quintiles					
	Low D1	D2	D3	D4	High D5	D1-D5
Holdingperiod 1m	1.20	1.15	0.94	0.75	0.38	0.82**
t-statistic						(2.39)
Holdingperiod 3m	1.16	1.13	0.97	0.84	0.57	0.59*
t-statistic						(1.79)
Holdingperiod 6m	1.16	1.13	1.09	0.99	0.69	0.47*
t-statistic						(1.65)

*** p<0.01, ** p<0.05, * p<0.1

E. Equally Weighted Factors

In this subsection we form equally weighted factor portfolios (instead of value-weighted) for the regression analysis. We want to make sure that our regression analysis is robust to changes in methodology. Table X shows the regression output for the zero-cost portfolios (return differentials) from Section III. We see that the D1-D5 portfolio has an estimated alpha of 0.61% in the four-factor model which is smaller than the 0.82% in Section III. The estimated alphas for the S1D1-S1D4, S2D1-S2D4, S3D1-S3D4 and S3D1-S1D4 portfolios in the four-factor model are 1.03%, 0.68%, 0.33% and 0.8% respectively. These alphas are also smaller than in Section III. Thus, the alphas are lower when using equally weighted factor portfolios. Nevertheless, the zero cost portfolios (except for large stocks) are still statistically significant at the 5% level.

Table X

Robustness Check- Equally Weighted Factors

This table shows the regression output of the Fama French (1993) three-factor model and the Carhart (1997) four-factor model on the zero-cost portfolios (returns differentials) from Section III. D1-D5 is a zero-cost portfolio with a long position in low dispersion stocks (D1) and a short position in high dispersion stocks (D5). S1D1-S1D4, S2D1-S2D4 and S3D1-S3D4 are zero-cost portfolios with a long position in low dispersion stocks (D1) and a short position in high dispersion stocks (D4) for small cap, mid cap and large cap respectively. S3D1-S1D4 is a zero-cost portfolio with a long position in large stocks with low dispersion and a short position in small stocks with high dispersion.

$$R_{it} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i[SMB_t] + h_i[HML_t] + m_i[WML_t] + \varepsilon_{it}$$

In the Fama French three-factor model the WML factor is excluded from the regression. R_i is the return on the zero-cost portfolios from Section III. $R_m - R_f$ is the equally weighted excess return on our proxy for the market portfolio. The risk-free rate is the Swedish one month Treasury-bill rate. SMB is the equally weighted return on a portfolio with small stocks less the equally weighted return on a portfolio with large stocks. HML is the equally weighted return on a portfolio with high BE/MV less the equally weighted return on a portfolio with low BE/MV. WML is the equally weighted return on a portfolio with high returns from τ-12 to τ-2 less the equally weighted return on a portfolio with low returns from τ-12 to τ-2. The sample period is January 1996 to March 2015. The number of observations is 229. The *t*-statistics in parentheses are based on Newey-West standard errors.

	Alpha	Risk Factors				Adj. R^2
Portfolio	(%)	$R_m - R_f$	SMB	HML	WML	(%)
D1-D5	0.68***	-0.37***	-0.77***	-0.24***		55.70
	(2.68)	(-8.56)	(-6.37)	(-3.97)		
	0.61**	-0.35***	-0.73***	-0.22***	0.07	55.98
	(2.16)	(-8.56)	(-6.62)	(-3.28)	(1.10)	
S1D1-S1D4	1.11***	-0.34***	-0.51***	-0.33***		29.83
	(3.86)	(-5.54)	(-3.20)	(-3.68)		
	1.03***	-0.32***	-0.47***	-0.31***	0.08	29.97
	(3.14)	(-5.57)	(-3.06)	(-2.99)	(0.86)	
S2D1-S2D4	0.75***	-0.34***	-0.54***	-0.12		30.97
	(2.63)	(-6.55)	(-5.08)	(-1.41)		
	0.68**	-0.32***	-0.50***	-0.10	0.08	31.12
	(2.29)	(-6.70)	(-4.43)	(-1.14)	(0.98)	
S3D1-S3D4	0.43	-0.44***	-0.17	-0.08*		35.57
	(1.44)	(-10.16)	(1.58)	(-1.72)		
	0.33	-0.42***	-0.12	-0.05	0.10	36.19
	(1.02)	(-10.11)	(-1.27)	(-1.08)	(1.47)	
S3D1-S1D4	0.88***	-0.35***	-1.42***	-0.39***		60.60
	(2.94)	(-6.37)	(-10.86)	(-4.53)		
	0.80**	-0.34***	-1.38***	-0.37***	0.07	60.68
	(2.44)	(-6.41)	(-10.80)	(-4.11)	(0.94)	

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

F. Subperiod Analysis

In this subsection we calculate the average monthly returns for the five portfolios sorted by dispersions in analysts' earnings forecasts for the subperiods 1996 to 2004 and 2005 to 2014. The D1-D5 portfolio has a return of 0.55% for the 1996 to 2004 period but is statistically insignificant. For the 2005 to 2014 period the D1-D5 portfolio has a return of 1.06% and is statistically significant at the 1% level. Thus, we see that the negative relation between dispersion in analysts' earnings forecasts and future returns is most pronounced in the second subperiod.

Table XI

Subperiod Analysis

This table shows equally weighted average monthly returns for five portfolios (with an equal number of stocks) which each month are formed based on the level of dispersion in analysts' earnings forecasts as of the previous month τ-1. The dispersion in analysts' earnings forecasts is defined as the standard deviation of net income forecasts divided by the absolute value of the mean of the same forecasts. Each firm is covered by two or more analysts, has a stock price of at least 10 SEK and a market value of 150 million SEK or more. Financial firms and firms with negative book equity are excluded. The table shows the returns for two subperiods as well as for the entire time period. All firms have been traded on the Stockholm, Oslo or Copenhagen Stock Exchange. The *t*-statistic in parenthesis is based on Newey-West standard errors. The table also shows the median dispersion in analysts' earnings forecasts for the two subperiods as well as for the entire time period.

Mean Returns						
	Dispersion Quintiles					
	Low D1	D2	D3	D4	High D5	D1-D5
1996-2015	1.20	1.15	0.94	0.75	0.38	0.82**
t-statistic						(2.39)
1996-2004	1.18	1.16	0.80	0.73	0.63	0.55
t-statistic						(0.98)
2005-2014	1.21	1.15	1.06	0.78	0.15	1.06***
t-statistic						(2.62)

*** p<0.01, ** p<0.05, * p<0.1

Median Dispersion						
	Dispersion Quintiles					
	Low D1	D2	D3	D4	High D5	All stocks
1996-2015	3.40	7.52	12.84	22.97	60.84	12.84
1996-2004	3.99	9.20	15.31	26.60	67.14	15.30
2005-2014	3.13	6.72	11.33	20.57	55.71	11.33

Table XI also shows the median level of dispersion in analysts' earnings forecasts for the two subperiods. We see that the median dispersion has decreased over time. We use the median to measure the change in dispersion since our sample contains firms with very high levels of dispersion.

The negative relation between dispersion in analysts' earnings forecasts and future returns is more pronounced in the second subperiod even though the median dispersion has decreased over time. This finding is inconsistent with the view that the negative relation between dispersion in analysts' earnings forecasts and future returns disappears over time due to decreasing short sale costs and less investor uncertainty.

VI. Conclusion

We show that the relation between dispersion in analysts' earnings forecasts and future returns is monotonically decreasing on the Scandinavian stock markets. This relation is most pronounced for small stocks (stocks with high short sale constraints). The results support the Miller (1977) argument that differences of opinion in the presence of short sale constraints lead to overvaluation. The regression analysis shows that exposures to beta, size, book to market and momentum cannot account for any of the return differential between low and high dispersion stocks. The regression analysis is robust to changes in methodology. Moreover, we show that the negative relation between dispersion in analysts' earnings forecasts and future returns is not driven by outliers or by firms covered by only two analysts.

The results are inconsistent with the view that the negative relation between dispersion in analysts' earnings forecasts and future returns disappears over time due to decreasing short sale costs and less investor uncertainty. Indeed, our subperiod analysis shows that the negative relation gets more pronounced over time even though the dispersion in analysts' earnings forecasts decreases over the sample period.

The results have direct implications for traders and regulators. For traders, zero-cost portfolios with a long position in low dispersion stocks and a short position in small, high dispersion stocks yield abnormal returns. In fact, a zero-cost portfolio with a long position in large, low dispersion stocks and a short position in small, high dispersion stocks generate a return as high as 16,2% per year. These strategies are, however, high turnover strategies, which require short positions in small stocks. Many small stocks cannot be shorted (and lack traded options) and even if they can be shorted there are high fees and other indirect costs associated with a short sale. As an alternative, investors can buy low dispersion stocks and avoid high dispersion stocks. This rather low turnover strategy might be more profitable.

Today, instead of avoiding high dispersion stocks, price insensitive index funds help optimists to absorb the outstanding shares of these stocks which lead to overvaluation and lower future returns. How traders optimally exploit these predictable patterns in returns is an interesting area for future research.

Regulators- if we consider market quality as their main objective- should try to reduce short sale constraints. Not only do short sale constraints lead to lower liquidity, higher volatility and higher spreads (Beber and Pagano (2013) and Boehmer, Jones and Zhang (2013)), short sale constraints also seem to reduce market efficiency.

We obtain the results in this thesis despite excluding small, illiquid stocks for which the negative relation between dispersion in analysts' earnings forecasts and future returns should be most pronounced. In addition, a more aggressive breakdown of portfolios (e.g. form ten portfolios based on dispersion in analysts' earnings forecasts instead of five) would probably reveal a subset of even more overvalued stocks. Thus, we conclude that the Miller (1977) argument is still valid and that analyst disagreement is still - a recipe for disaster.

REFERENCES

Artmann, S. et al., 2012. The Cross-Section of German Stock Returns: New Data and New Evidence. *Schmalenbach Business Review, 64,* pp. 20-43.

Banz, R. W., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics,* 9(1), pp. 3-18.

Beber, A. & Pagano, M., 2013. Short-Selling Bans Around the World: Evidence from the 2007–09 Crisis. *The Journal of Finance,* 68(1), pp. 343-381.

Black, F., Jensen, M. C. & Scholes, M., 1972. The Capital Asset Pricing Model: Some Empirical Tests, In M. Jensen, ed.: *Studies in the Theory of Capital Markets* (Praeger)

Boehme, R. D., Danielsen, B. R. & Sorescu, S. M., 2006. Short-Sale Constraints, Differences of Opinion, and Overvaluation. *Journal of Financial and Quantitative Analysis,* 41(2), pp. 455-487.

Boehmer, E., Jones, C. M. & Zhang, X., 2013. Shackling short sellers: the 2008 shorting ban. *The review of financial studies,* 26(6), pp. 1363-1400.

Carhart, M. M., 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance,* 52(1), pp. 57-82.

Conrad, J. S. & Kaul, G., 1993. Long-term market overreaction or biases in computed returns?. *The Journal of Finance,* 48(1), pp. 39-63.

D'Avolio, G., 2002. The market for borrowing stock. *Journal of Financial Economics,* 66(2-3), pp. 271-306.

Danielsen, B. R. & Sorescu, S. M., 2001. Why Do Option Introductions Depress Stock Prices? A Study of Diminishing Short Sale Constraints. *Journal of Financial and Quantitative Analysis,* 36(4), pp. 451-484.

De Bondt, W. F. M. & Thaler, R., 1985. Does the stock market overreact?. *The Journal of Finance,* 40(3), pp. 793-805.

Diamond, D. W. & Verrecchia, R. E., 1987. Constraints on short-selling and asset price adjustment to private information. *Journal of Financial Economics,* 18(2), pp. 277-311.

Diether, K. B., Malloy, C. J. & Scherbina, A., 2002. Differences of Opinion and the Cross Section of Stock Returns. *The Journal of Finance,* 57(5), pp. 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), pp. 3-56.

Fama, E. F. & French, K. R., 1996. Multifactor Explanations of Asset Pricing Anomalies. *The Journal of Finance,* 51(1), pp. 55-84.

Gibbons, M. R., Ross, S. A. & Shanken, J., 1989. A Test of the Efficiency of a Given Portfolio. *Econometrica,* 57(5), pp. 1121-1152.

Ince, O. S. & Porter, R. B., 2006. Individual equity return data from Thomson Datastream: Handle with care!. *Journal of Financial Research,* 29(4), pp. 463-479.

Jegadeesh, N., 1990. Evidence of Predictable Behavior of Security Returns. *The Journal of Finance,* 45(3), pp. 881-898.

Jegadeesh, N. & Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *The Journal of Finance,* 48(1), pp. 65-91.

Lee, C. M. & Swaminathan, B., 2000. Price Momentum and Trading Volume. *The Journal of Finance,* 55(5), pp. 2017-2069.

Miller, E. M., 1977. Risk, Uncertainty, and Divergence of Opinion. *The Journal of Finance,* 32(4), pp. 1151-1168.

Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns. *Journal of Financial Economics,* 78(2), pp. 277-309.

Patton, A. J. & Timmermann, A., 2010. Monotonicity in asset returns: new tests with applications to the term structure, the CAPM, and portfolio sorts. *Journal of financial economics,* 98(3), pp. 605-625.

Saffi, P. A. C. & Sigurdsson, K., 2011. Price Efficiency and Short Selling. *The Review of Financial Studies*, 24(3), pp. 821-852.

Stattman, D., 1980. Book values and expected stock returns. *The Chicago MBA: A Journal of Selected Papers, 4,* pp. 25-45.

Viale, A. M., Kolari, J. W. & Fraser, D. A., 2009. Common risk factors in bank stocks. *Journal of banking & finance,* 33(3), pp. 464-472.

Appendix A. Description of Variables

Table A1

Description of Variables

This table shows the Thomson Reuters Datastream (TRD) variables used in this thesis together with its corresponding code (mnemonic) and code description. The code description is taken from TRD.

Variables	TRD Code	Code Description
Dispersion in Analysts' Earnings Forecasts	INC1CV	Coefficient of variation of all the FY1 estimates. A measure of the spread of the estimates in terms of the standard deviation.
Number of Forecasts	INC1NE	Total number of estimates associated with the FY1 forecast.
Market Value	MVC	The consolidated market value of a company.
Stock Price	P	Represents the official adjusted closing price.
Return Index	RI	Shows a theoretical growth in value of a share holding over a specified period, assuming that dividends are re-invested to purchase additional units of an equity or unit trust at the closing price applicable on the ex-dividend date.
Common Equity	WC03501	Represents common shareholders' investment in a company.
Preferred Stock	WC03451	Represents a claim prior to the common shareholders on the earnings of a company and on the assets in the event of liquidation.
Deferred Taxes	WC03263	Represent the accumulation of taxes which are deferred as a result of timing differences between reporting sales and expenses for tax and financial reporting purposes.