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The Impact of the Precision and Scale of News on Trading Volume: Evidence from Volume Following Profit Warnings

Abstract

We contribute new empirical evidence on the determinants of trading volume for stocks. First, we investigate whether the precision of the information in a public announcement affects volume. We compare volume following profit warnings that offer a new quantitative earnings forecast with volume following those that simply announce that earnings will fall short of expectations. Second, for the sample of warnings that include a quantitative forecast, we examine the impact on volume of the size of the earnings surprise. We find that volume is higher following warnings that include a new earnings forecast, and higher the larger is the surprise.

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1. Introduction

To many observers the level of trade on stock markets appears excessive, see for example the discussion in Dow and Gorton (1997). For example turnover data on the NYSE implies that the average share is held for well under two years[1]. Given the costs of trade to investors this seems to be a surprisingly short holding period and a natural question to ask is whether this scale of trading is rational. In order to address this issue we need to understand exactly why investors trade. In particular can trade be explained by rational disagreement between investors about fundamental value or are instead investors subject to behavioural biases, for example overconfidence, which cause them to trade too intensively for their own good, Odean (1998, 1999)[2]?

The assumption that agents simply receive different private signals might seem a natural way to rationally explain trade but when this idea is subjected to formal scrutiny it proves that different private signals alone cannot explain trade if the private signals are drawn from a fixed distribution that is common knowledge, Aumann (1976). Evidence of a substantial increase in trading volume associated with public announcements also casts doubt on this simple explanation, for example Ryan and Taffler (2004). A public announcement should level the information playing field and so on this account it should if anything reduce, and certainly not increase, trading volume.

Considerable effort has gone into developing different models that are consistent with the evidence that public announcements generate trade. Disagreement inevitably plays a

[1] See the NYSE website.
[2] Another question, examined by Dow and Gorton (1997), is the incentives for agents to trade under optimal contracts with delegated portfolio management.

central role but it is motivated in a more sophisticated way than simply assuming different private signals are drawn from a common distribution. Trading volume can increase following public news for two distinct reasons in this theoretical literature. In one class of model the public news is assumed to itself introduce a new source of disagreement, Karpoff (1986), Kandel and Pearson (1995). For example some investors may view the announced failure of a take-over bid as good news and others view it as bad news because each group has a different model of what drives earnings growth. Another reason for disagreement may be that investors have different information processing abilities, Kim and Verrecchia (1997). A rather different reason for trade following public news is that investors have different degrees of confidence in earlier private signals. When a public signal arrives after private signals there is a common interpretation of the news, but Bayesian updating results in differences in the extent to which beliefs change, because of the differences in the precision of priors, and this generates trade, Kim and Verrecchia (1991).

Different ways of testing these models have been explored. Both classes of model predict that on days when there is public news there should be positive relationship between the size of the surprise and trading volume. If the size of the surprise is measured by abnormal returns on the day of the announcement then this prediction can be tested using data on volume and returns. It is confirmed by overwhelming evidence of a positive relation between the absolute size of returns and volume on days of public announcements, for surveys see for example Kandel and Pearson (1995) and Karpoff (1987). A more discriminating test is offered by evidence that even announcements that bring virtually no net news, measured by abnormal returns on the day of the news, nevertheless generate substantially higher volume than days with no public news, see for example Bamber and Cheon (1995), Kandel and Pearson (1995). This observation is consistent with models that assume that the public news brings a new source of disagreement, for example Kandel and Pearson (1995), but not with models that assume volume is driven by Bayesian updating in the context of heterogeneous precisions of prior beliefs.

Another approach to testing models of trade is to look at the relation between volume at earnings announcements and the dispersion in beliefs. The model developed by Kim and Verrecchia (1991) implies that increased dispersion of prior beliefs results in increased volume at the date of the public signal. Several studies have tested this proposition, using the dispersion in analysts' forecasts as the dispersion measure. Atiase and Bamber (1994) and Bamber, Barron and Stober (1997) find that trading around scheduled earnings announcements is increasing in measures of prior disagreement. Another test is to examine how the dispersion of beliefs changes after the public signal, Kandel and Pearson (1995). If announcements themselves introduce a new source of disagreement then we should expect to see the relative rankings of different investors' expectations change after the public signal, but the relative ranking should not change under the common interpretation assumption. Kandel and Pearson (1995) find evidence for these reversals, sometimes called "belief jumbling", and infer this to be support for the differential interpretation model.

In this paper we contribute new empirical evidence that may be used to assess models of volume. Using data on volume following profit warnings, we firstly investigate whether the precision of the news affects trading volume. The impact of precision on volume is a topic that has not been previously explored in the empirical literature, although an effect is predicted explicitly in Kim and Verrecchia (1991), proposition 3**,** and is implicit in models that assume public news is itself a source of disagreement. More precise news should be associated with less volume in the latter class of models since the more precise the news the less is the opportunity for disagreement. Profit warnings allows us to examine the effect of precision because profit warnings fall into two classes, those that provide new quantitative guidance and those that simply state that earnings will be below the current market expectations. We will refer to these two classes as quantitative warnings and qualitative warnings and judge the impact of precision by comparing volume following these two types of warning.

A potential problem in a simple comparison of volume following these two classes of warning is that qualitative warnings might on average be perceived as better (or worse) news than the average quantitative warning and if perceived scale of the news is correlated with volume then the impact of precision alone cannot be inferred from a simple comparison. Kasznik and Lev (1995) argue that managers facing a significant negative EPS surprise issue a "hard" announcement including a new earnings forecast. Comparatively softer surprises are dealt with by issuing either a qualitative warning or no warning at all. On the other hand Bulkley and Herrerias (2005) find that abnormal returns when qualitative warnings are announced are significantly more negative than for the average quantitative warning, implying that qualitative warnings are initially perceived as worse news. In order to control for the perceived size of the surprise we compare volume following the two classes of warning using only that subset of quantitative warnings that have the same average abnormal returns in the announcement window as the average qualitative warning. We explain our method in detail in section 3.

The second type of evidence we report is on the relation between volume and the scale of the news. The models reviewed above imply a positive relationship between the size of the surprise and volume but evidence for this prediction usually comes from a correlation between volume and abnormal returns, which may be assumed to be a proxy for the size of the surprise. A problem with measuring the size of the surprise by abnormal returns is that volume and abnormal returns are determined simultaneously and therefore we cannot rely on inference in a regression test estimated by OLS where we control for other potential determinants of volume. We cannot easily control for the endogeneity of abnormal returns using two-stage least squares in this context because there will be no instrument for abnormal returns in an efficient market. Profit warnings offer a chance to test a hypothesis about volume using an objective measure of size of the news, rather than its perceived size measured by abnormal returns, because the scale of the news may be measured in our sample by the difference between the previous market forecast and the new forecast issued by the firm in the warning. An advantage of measuring size directly is that problems of simultaneity are avoided so that inference using OLS to estimate a model of volume is possible.

In section 3 we set out an empirical model of trading volume on days of news announcements that controls for the variables that other authors have found to be important determinants of trading volume around information events. We include a dummy variable to reflect the type of warning and infer the effect of precision on volume from the estimate and significance of the coefficient on this dummy variable. We describe the data in section 2, results are reported in section 4 and section 5 concludes.

2. Profit warnings

The data set used in this study consists of public announcements by US firms that are issued when firms expect an earnings per share, EPS, outcome that will be below the current market consensus. There is often discretion, and hence debate, over whether a particular statement should actually be described as a "profit warning". Our data consists of statements that were listed as "profit warnings" on the CNN site, www.cnn/markets/IRC/warnings.htlm. The profit warnings studied here span from late February 1998 up to October 31st 2000 and in this period 2446 warnings were recorded.

The warnings dataset includes the date of the warning, the firm issuing the warning, the earnings' announcement that is the subject of the warning, the previous EPS forecast, and the new forecast, as seen in the following example of how the information is recorded on the CNN site:

Date	Company Name	Ticker	Period	Pre-estimate	Warning
April 14, 1998	MEMC Elec	WFR	Q1	($0.55)	Loss $0.72
April 14, 1998	SMC Corporation	SMCC	Q1	$0.23	Below estimate
April 15, 1998	Alliance Gaming	ALLY	Q3	$0.30	$0.05-0.06

It is worth noting that, the previous EPS forecast is always an accurate point estimate, for example *"$0.5 per share*". The warnings issued were far from being uniform. More specifically, the warnings take the following forms:

- Point estimates : e.g. "*Earnings will be $0.5 per share*"
- Open ranges : e.g. "*Earnings will be less than/ no more than $0.5 per share*"
- Closed ranges : e.g. "*Earnings will be $0.3-$0.7 per share*"
- Qualitative : e.g. "*Earnings will be less than expected*"

The first 3 categories are **quantitative** warnings, since they always contain a new numerical estimate of EPS. The last is classified as **qualitative.** These give a qualitative description of the new EPS estimate, and may include quantitative facts for the firms' operation, but not directly linked to an EPS estimate. For example a warning that quantifies losses on a particular contract or in a particular market or operational division, but does not offer a new EPS forecast, will be described as qualitative. We recorded 747 qualitative warnings and 1699 quantitative warnings in the sample period.

We report in Table 1 the distribution of profit warning announcements throughout the timeline of the sample used here. Note that there is a significant increase in the number of profit warnings in September/October 2000, due to revised disclosure regulation, regulated Federal Disclosure, which was announced in August 2000 in the U.S.

[Table 1.]

Trading volume and returns data for the warning companies were collected from CRSP and market wide data were collected from DATASTREAM for NYSE/AMEX trading volume for the period between February 1998 and October 2000.

3. Hypotheses and methodology

In this section we set out the specification of the tests and describe how the variables used are constructed. We are interested in testing two hypotheses and we describe the methodology for each in the following two sub-sections.

3.1 HI: Trading volume on the day of public news is lower when the news is less precise.

This is an explicit prediction, proposition 3, of Kim and Verrecchia (1991). Models where volume is driven by disagreement over the interpretation of the news do not yield formal predictions for the effect of precision on volume. However it seems very much in the spirit of this idea that *more* volume should be observed when news is less precise since the less precise the news the greater the scope for disagreement. We test H1 by examining whether trading volume is significantly different following quantitative and qualitative warnings.

There are different approaches that might be applied to testing hypotheses about the determinants of abnormal volume. One approach involves first constructing a benchmark for normal volume and then testing hypotheses using abnormal volume measured as the difference between actual volume and expected volume measured as this benchmark, for example Ryan and Taffler (2004). Tkac (1999) surveys the issues involved in constructing such a benchmark. For example Tkac discusses the relative importance that past firm volume and market volume should have in a benchmark. However rather than applying a two-step procedure where a model of expected volume is estimated at the first stage, we adopt a regression framework where variables that would otherwise be included in the benchmark enter explicitly as regressors.

We test H1 using a cross-section regression of abnormal trading volume, ABV, measured as the ratio of event volume to average daily volume over the last six months, on a dummy variable that reflects the type of warning and three other control variables: lagged abnormal volume, market abnormal volume, and firm size. We estimate the regression by Ordinary Least Squares since the right hand side variables can all be assumed to be exogenous, and profit warnings from different firms are rarely issued on the same day so that there is no reason to be concerned about cross-sectionally correlated errors that often beset empirical work in finance.

We estimate the regression:

$$ABV_{t,t+1} = a_1 ABV_{t-1} + a_2 SIZE + a_3 ABV_{NYSE,t,t+1} + a_4 D_1 \qquad (1)$$

The variables are defined in detail below and the dummy variable takes the value 1 for a qualitative warning and zero otherwise. In evaluating the effect of precision on trading volume it is important for unbiased inference that the dummy variable is not correlated with the perceived size of the surprise since the perceived size of surprise is likely to be correlated with the dependent variable, as we discussed in the introduction.

We ensure that the average perceived surprise is the same, whether the dummy variable takes the value of unity or zero, by the following procedure. We include in the regression test all firms where a qualitative warning was issued but only include the sub-sample of quantitative warnings that by selection have the same average abnormal returns in the announcement window as the average abnormal return for qualitative warnings. We implement this idea by first recording the abnormal return on each warning in the 2-day announcement window. The average abnormal return on the sample of qualitative warnings is -25.1% and the average abnormal return on quantitative warning is only –20.9%. We therefore eliminate quantitative warnings from our sample for this test, starting with that which has the least negative abnormal returns and continuing to eliminate successively more negative warnings until the average abnormal returns on the quantitative sample remaining falls to –24.9%[3]. We now have a sample of quantitative warnings that on average are perceived as equally bad news as the sample of qualitative warnings, so that statistical inference on the impact of precision can be based on an OLS estimate of the slope coefficient on the dummy variable in equation (1)[4].

The other variables in regression (1) are defined and constructed as follows:

Abnormal trading volume for the warning firm, $ABV_{t,t+1}$

Event abnormal volume is measured as average abnormal volume over the day of the profit warning announcement (t) and the day following the announcement (t+1) relative to average daily volume over the last six months. We use a two-day window because some companies issue profit warnings after the closure of the market. One could measure volume as the percentage of outstanding shares that are traded on the event day, following for example Collett (2004). The advantage of our measure, pointed out by Bamber and Cheon (1995) who use a similar ratio to measure abnormal trading volume, is that this method controls for cross-sectional differences in turnover between stocks.

[3] An alternative procedure would be to eliminate quantitative warning on the criterion of the size of the earnings surprise, starting with the smallest surprise, and continue eliminating warnings that are successively larger surprises until again the average abnormal return for the remaining quantitative warnings was the same as the average abnormal returns on the qualitative warnings. An advantage of this procedure is that the criterion for exclusion is an exogenous characteristic, but the disadvantage is that this method results in a smaller remaining sample of quantitative warnings.

[4] Another way to control for the size of the surprise that might be considered is to include the size of the surprise as a regressor in equation (1). However the only way to measure the size would be by abnormal returns and including abnormal returns as a regressor in equation (1) would violate the assumptions required for OLS since volume and abnormal returns are determined simultaneously and two-stage least squares suffers from the problems described in the introduction.

For example bid-ask spreads and the percentage of shares owned by directors and by institutions might all affect turnover both at announcements and on non-event days, Utama and Cready (1997).

Size of the firm that issues the warning

We measure size as the average market capitalisation of the warning company in the warning month. Several studies have found size to be a significant determinant of turnover on the average trading day, although different results have been obtained. For example Llorente et al. (2002) find that turnover is greater for larger firms but Tkac (1999) finds empirical evidence for a negative relationship between firm size and volume. However since we are scaling event turnover by average recent turnover this direct source of size effects will cancel out in our specification. However there are other reasons why a profit warning from a small firm may elicit a more pronounced reaction. For example it is hypothesised and verified by Jackson and Madura (2003) that smaller firms have fewer information leaks before announcements. Also there will be more publicly available information for larger firms produced by external parties. For example size is correlated with the number of analysts following a stock. As Baginski and Hassel (1997) point out, if these external parties produce enough information to meet the demand, then a profit warning and the external information collection could act as substitutes to each other. This would imply a higher volume following a warning from a small firm. If there are behavioural determinants of abnormal volume one might also expect abnormal volume to be decreasing in size since when abnormal returns are found for news events, and explained by behavioural biases, it is often found that these are more significant for smaller firms.

Firm's abnormal trading volume for the previous day of the warning

It is typically found that volume is serially correlated, for example Llorente et al. (2002), and therefore this is included as a control variable in our model of event volume.

Abnormal trading volume of the market for the day of the announcement

Abnormal market volume is used as a proxy for a macro-effect that can be present in the reaction to a firm's profit warning, see for example Tkac (1999) who shows the importance of controlling for aggregate market volume. Since we have scaled firm event volume by average daily volume over the last six months we need to measure market volume in a consistent way. It is measured as the average market volume on the NYSE over the two-day window, relative to average volume over the last six months. That is abnormal volume, $ABV_{NYSE,t,t+1} = \frac{V_{NYSE,t} + V_{NYSE,t+1}}{2\bar{V}_{NYSE,6}}$

3.2 H2: If a new earnings forecast is issued trading volume is higher the larger is the size of the surprise.

This hypothesis is tested by OLS estimation of the following regression applied to the full sample of firms that issued a quantitative warning.

$$ABV_{t,t+1} = a_1 \frac{(O-N)}{\bar{P}_{month}}(1-D_1) + a_2 D_1 + a_3 ABV_{NYSE,t,t+1} + a_4 SIZE + a_5 ABV_{t-1} + a_6 \qquad (2)$$

Estimating regression (2) requires discussion of the construction of one new variable, the size of the earnings surprise.

The size of the earnings surprise.

We measure the new earnings estimate, N, for quantitative forecasts as either the point estimate, mid-point if closed range is specified, or end point of open ended range. Let ***O*** be the pre-announcement consensus EPS estimate of the market, reported on the same CNN site. The EPS surprise, *O-N,* will always be positive since by construction we have a sample where the new forecast is bad news. The absolute surprise needs to be scaled since absolute changes in EPS will depend in an arbitrary way on the absolute size of the EPS. We need a measure of the relative size of the surprise. One might scale the change in forecast by the old forecast, following for example Damodaran (1989), but when the old forecast was zero the observations have to be dropped. Even if one accepts loosing some observations, another problem with this method is that when the old forecast is very close to zero the regressor takes on extreme values. We therefore scale the change in the EPS by the stock price in order to obtain a measure of the relative size of the earnings surprise. The average stock price for the month of the announcement was used as the weighting factor because of the volatility of daily prices around profit warnings. The news variable is then multiplied by $(1-D_1)$, where D_1 represents the qualitative warnings' variable, taking the value 1 when there is a qualitative warning and 0 otherwise.

4. Results

HI: Trading volume on the day of a public announcement is higher when the news is more precise.

The results from estimating regression (1) that tests this hypothesis are reported in Table 2.

[Table 2 here]

As we explained above, the results reported in Table 2 are for the sub-sample of quantitative warnings that have the same average announcement abnormal returns as the average of the abnormal returns following qualitative warnings. We see clear evidence in Table 2 that the volume of trade when investors receive a profit warning that includes a new quantitative EPS forecast is significantly greater than when they receive only qualitative guidance. Therefore, the H1 hypothesis is accepted: quantitative profit warnings result is significantly greater volume of trade, holding constant the average perceived size of the surprise in each class.

The signs on the control variables are all as expected. The lagged abnormal volume and abnormal volume on the market are both significant and positively correlated with abnormal volume on the announcement day. The coefficient on size is of the sign that is expected if surprises are on average relatively bigger for smaller firms, although it is not significant. We experimented with log-linear and semi-log specifications but in no case did firm size become significant.

H2: If a new earnings forecast is issued trading volume is higher the larger is the size of the surprise.

In table 3 we report the results from estimation of regression (2) whose specification was motivated in sub-section 3.2.

[Table 3 here]

Consistent with predictions of models of rational trade, the larger is the surprise the greater is the trading volume. This is not surprising given existing evidence of a positive correlation between abnormal returns and volume, but it is re-assuring to see these results confirmed when the surprise is measured explicitly and in a multivariate model where we have controlled for the other determinants of trading volume.

We report in table 4 results to confirm the robustness of our results to our specification. It can be seen that the significance of our results is not sensitive to the particular specification and we also report, without including the tables here, that working with a log-linear model also made no substantial difference to the significance of these results.

[Table 4 here]

5. Conclusions

In this study we have shown that when news is more precise it generates more trade, consistent with the predictions of Kim and Verrecchia (1991). On the other hand these results are not easily reconciled with models that explain greater trade on days of public news as a result of the differential interpretation of the news. Although formal results for the impact of the precision of the news on volume are not reported for these models it is in the spirit of differential interpretation that less precise signals should engender more trade. If the increased trade is a result of disagreement over the meaning of the news then the more precise the news the less the scope for disagreement, and the lower should be the volume.

Although the results we report on precision are consistent with one model of rational trade they are also consistent with some behavioural models of trade. Whether or not agents are overconfident, Odean (1998, 1999), the extent to which they revise their beliefs in response to new information may also depend on the nature of that information. Agents subject to the "anchoring and conservatism bias", Kahneman & Tversky (1974), may respond differently to quantitative warnings than to qualitative warnings. According to this bias agents appear to "anchor" on their initial forecasts/valuations, and they make insufficient adjustments when they receive new contrasting information, particularly if it is not quantitative. A quantitative profit warning presents them with a new numerical anchoring point, making the comparison to prior forecasts more clear, whereas a qualitative warning has a less obvious anchoring point. The expected outcome is that agents will act more confidently, so that more trading is expected, when presented with a strong new anchoring point. The results reported here complement experimental results for asset markets that show that agents are more confident in their decision-making processes for buying/selling stocks upon receiving new information when this information is precise (quantitative), Hirst, Koonce and Miller (1999).

Our second result is that larger surprises are associated with more volume and this is consistent with the models of rational trade. There is already empirical support for this prediction inferred from evidence of a positive relationship between abnormal returns and volume. However it is encouraging that the prediction is confirmed when the size of the surprise is measured objectively, rather than proxied by abnormal returns, and when we control for other determinants of trading volume.

The comment by some observers that trading volume seems to be unduly high can ultimately only be evaluated using a calibrated model of rational trade but the first step in this challenging task is to determining whether existing models of rational trade are consistent with the data. In this paper we have tested the predictions that models of rational trade make for trading volume following public announcements. We find that the response of volume to the scale and precision of profit warnings is consistent with different models of rational trade that have been proposed.

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Tables

Table 1.

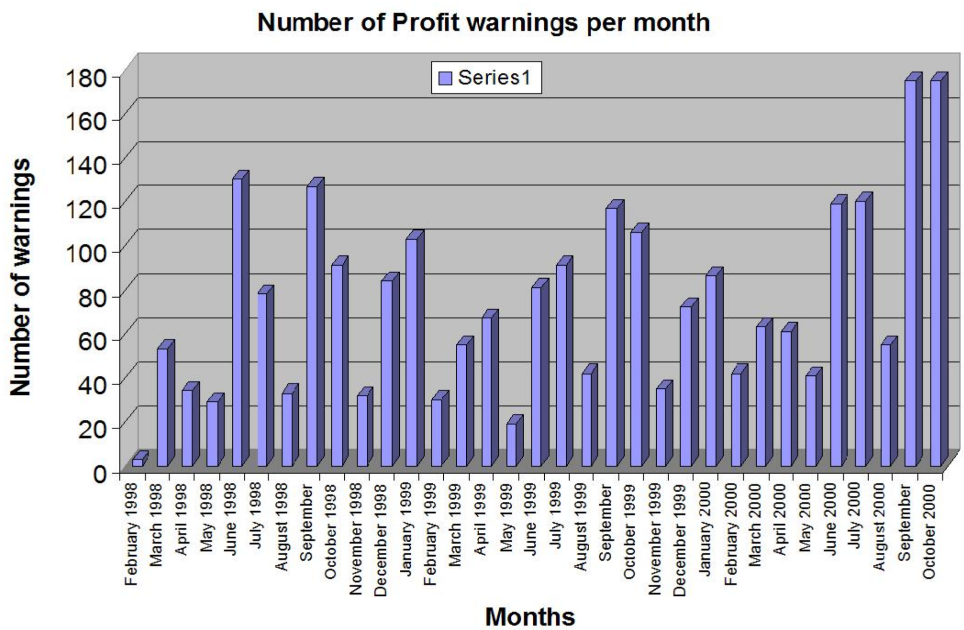

Table 2

$ABV_{t,t+1} = a_1 ABV_{t-1} + a_2 SIZE + a_3 ABV_{NYSE,t,t+1} + a_4 D_1 + a_5$					
Coefficient	Lagged Abnormal volume, a_1	Firm Size, a_2	Market Abnormal Volume, a_3	Qualitative Dummy, a_4	Intercept, a_5
Estimate	1,16	-1E-07	204,44	-17,47	24,36
t-stat	8,03	-1,23	2,19	-3,16	2,49
R-square	0,068				

Table 3.

$$ABV_{t,t+1} = a_1 \frac{(O-N)}{\bar{P}_{month}}(1-D_1) + a_2 D_1 + a_3 ABV_{NYSE,t,t+1} + a_4 SIZE + a_5 ABV_{t-1} + a_6$$						
Coefficient	Quantitative, a_1	Qualitative, a_2	Market Abnormal Volume, a_3	Firm Size, a_4	Lagged Abnormal Volume, a_5	Intercept, a_6
Estimate	222.83	-14.40	200.12	-8.55E-08	1.15	21,42
t-stat	2.40	-2.54	2.15	-1.01	8.00	2,18
R Square	0.070					

Table 4.

$$ABV_{t,t+1} = a_1 \frac{(O-N)}{\bar{P}_{month}}(1-D_1) + a_2 D_1 + a_3$$ **(4)**					
Coefficient	Quantitative, a_1	Qualitative, a_2	Intercept, a_3		
Estimate	228.48	-24.38	48,17		
t-stat	2.44	-7.98	23,33		
$$ABV_{t,t+1} = a_1 \frac{(O-N)}{\bar{P}_{month}}(1-D_1) + a_2 D_1 + a_3 ABV_{NYSE,t,t+1} + a_4$$ **(5)**					
Coefficient	Quantitative, a_1	Qualitative, a_2	Market Abnormal Volume, a_3	Intercept, a_4	
Estimate	224.00	-14.343	195.00	28,11	
t-stat	2.40	-2.50	2.07	2,83	
$$ABV_{t,t+1} = a_1 \frac{(O-N)}{\bar{P}_{month}}(1-D_1) + a_2 D_1 + a_3 ABV_{NYSE,t,t+1} + a_4 SIZE + a_5$$ **(6)**					
Coefficient	Quantitative, a_1	Qualitative, a_2	Market Abnormal Volume, a_3	Firm Size, a_4	Intercept, a_5
Estimate	215.69	-14.28	197.05	-8.41E-08	28,23
t-stat	2.30	-2.49	2.09	-0.98	2,85