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Impact of Analysts' Recommendations on Stock Performance

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ABSTRACT *This paper examines the effect of analysts' recommendations on stock return, volume and volatility. The study covers a sample of 36 large cap stocks traded on the US stock market over the period June 1997–May 2003. The empirical evidence suggests a significant impact of analysts' recommendations on the stock market. The research considers market microstructure and looks at the motivation and behaviour of analysts.*

KEY WORDS: Analysts' recommendations, stock returns, volume, volatility

1. Introduction

A firm's value and its risk depend directly on stock market perception. To a large extent investors' perception is formed under the pressure of analysts' recommendations. Brokerage companies spend a considerable amount of money to collect relevant information and transform it into a concise recommendation regarding position on a particular stock. This paper investigates whether there is an effect of changes in analysts' grades on stock performance. Under an efficient market hypothesis (Fama, 1970), there should be no effect of analysts' recommendations since the latter do not produce any qualitatively new information that would not be reflected in stock price. However, if there exists asymmetric information and a weak form of efficient market, recommendations may decrease asymmetries, promoting efficiency and resulting in a price adjustment.

Analysts typically issue recommendations that are based on a five-grade range, e.g. strong buy, buy, neutral, sell and strong sell. However, practitioners recognize that the grades are skewed upward and should be interpreted carefully. Partial explanation for the observed upward trend can be found by exploring the affiliations of analysts. Generally, they fall into three categories: sell-side analysts who work on full-service broker-dealers that also provide investment banking services for corporate clients including companies whose securities are analysed; buy-side analysts who work for institutional money managers and counsel their asset managers; independent analysts who are not directly associated with corporate or institutional clients. Sell-side analysts affiliated with investment corporations are subject to a considerable conflict of interests since profits of the corporate clients depend on analyst recommendations. Hong and Kubik (2003) conducted

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an extensive coverage of analysts' behaviour and found that brokerage houses reward optimistic analysts who promote stocks. An analysts' grading usually is compared to their peers' decisions at rival firms. The fear of being different drives herding behaviour and upward bias spreads over buy-side and, so-called, independent analysts. In order to avoid the upward trend in this research, an analysts' relative grade change is considered.

Another issue to address is the distribution and timing of analysts' recommendations. Nowadays diverse market information, including analysts' ratings, is available for individual investors for a small fee or even free of charge. An important timing aspect of those announcements, however, is almost never addressed. Rating changes issued by brokerage firms are typically released in two steps: institutional clients of the brokerage firm get the news first, the information later is disseminated to news and research agencies, which brings it to individual investors.

Many existing studies detected that analysts' recommendations do not produce abnormal returns. Fama (1998) denies the existence of long-term return abnormalities, but does not exclude the possibility of short-term abnormal returns. Womack (1996) concludes that the reaction to grade changes appears to be permanent not quickly mean-reverting. Besides, the study detects a strong upward trend in recommendations. In the analysis of portfolio built on the basis of recommendations Barber *et al.* (2001) revealed significant abnormal returns, which diminish, however, if transaction costs are properly measured.

Alongside a traditional event study of return abnormalities, this study also intends to tackle volatility and volume. Volatility is one of the major concepts in modern finance. It is widely applied in option pricing, portfolio managements and risk management. The first theoretical models (Merton, 1969; Black and Scholes, 1973) assumed constant volatility. Later studies recognized time-varying and predictable volatility, e.g. the ARCH model of Engle (1982), GARCH of Bollerslev (1986), and the stochastic volatility model of Melino and Turnbull (1990). As a contribution to the extensive literature on time-varying volatility this study relates increased volatility to the updates of analysts' recommendations.

Following Jones *et al.* (1994), volume can be used as a proxy for the number of transactions. The latter through the brokerage fees and commissions translates into profits for brokerage houses. This creates a direct incentive to influence volume. Clarks (1973) uses trading volume as a proxy for the speed of informational flow. Therefore, volume should strongly respond to analysts' recommendations if they create new market information. This fact has not been sufficiently covered in the literature and this research attempts to fill the gap in this area.

An additional emphasis in this research is put on the strength of recommendations under various scenarios, i.e. single versus multiple recommendations and homogeneous versus heterogeneous recommendations, which is also new to the literature.

Throughout the research we are talking about the effect of recommendations on stock performance. Since the possibility of a certain degree of endogeneity of recommendations is not fully ruled out, strictly speaking the words 'effect' and 'impact' should be interpreted in the terms of correlation rather then causality.

2. Methodology

Event study, as a method of measuring impact of particular event on stock price, has a long history. Examining stock splits Fama *et al.* (1969) developed methodology that became widely used in further research. The idea of event study is to determine abnormal returns associated with market events. Brown and Warner (1980, 1985) provide a comprehensive overview of recent methods used for event studies. From the series of Monte-Carlo simulations they conclude that mean-adjusted returns model performs as well as more complex market and risk adjusted returns model.

Relying on the above findings mean-adjusted returns model is applied in this research. Similar analysis is adopted to measure the abnormal volatility and volume and is described further in this section.

A random walk is generally accepted as a good approximation of log of price (Cootner, 1964). Consequently, return is defined as a difference in the logs of closing prices over the period of one day $\ln(P_t/P_{t-1})$ and excludes dividends.

Typically an intra-day volatility is not observable unless high frequency data are available. Alizadeh *et al.* (2002) revived the idea of range-based estimation of the volatility. Rogers and Satchell (1991) suggested a volatility estimator based on high, low, and closing prices normalized by opening price. The estimator is based on the assumption that the price process is following Brownian motion with drift. Let $P_{high,t}$, $P_{low,t}$, $P_{o,t}$ and P_t denote the high, low, opening and closing price from the day t respectively. Define,

$$H_t = P_{high,t}/P_{o,t} \quad S_t = P_t/P_{o,t} \quad L_t = P_{low,t}/P_{o,t}$$

$$Vlt_t = H_t(H_t - S_t) + L_t(L_t - S_t) \tag{1}$$

After a series of Monte Carlo simulations Rogers *et al.* (1994) found that their estimator (1) always outperforms naïve estimators of variance based on squared daily returns, and in the case of non-zero varying drift, the Garman and Klass (1980) estimator. The authors suggest further refinement of the estimator (1) to remove bias caused by shortening of the continuous price process to trading hours. However, the refinement only slightly improves the original estimator and requires the number of transactions, which is not readily available. Therefore, this paper adopts the original Rogers and Satchell volatility estimator (1).

Volume reflects the number of shares traded over a day and enters the numerical analysis in absolute terms.

The term 'performance' is applied further to denote return, volatility or volume in each particular case. The cross-sectional unit in this study is an event, i.e. an upgrade or downgrade in an analyst's recommendation regarding a particular stock. The time scale is transformed in the following manner. The day '0' is defined as an event day, days before with negative values as pre-event days and days after with positive values as post-event days. The abnormality AbX_i is measured on the basis of an average deviation from the normal performance NX_i over the cross-section of events i.

$$AbX_{i,t} = X_{i,t} - NX_i \tag{2}$$

The normal performance for each event is defined as an average over estimation period, i.e. sufficiently large number of pre-event days. The estimation period in this research is 100 days from the day −103 to day −4.

$$NX_i = \frac{1}{100}\sum_{t=-103}^{-4} X_{i,t} \tag{3}$$

Different estimation periods have been tested, but the results do not reveal sensitivity to the choice of the length if it is sufficiently long.

An average abnormal performance for N events is measured as following:

$$AAbX_t = \frac{1}{N}\sum_{i=1}^{N} AbX_{i,t} \tag{4}$$

Assuming that the abnormal performance over the cross-section is independently drawn from a finite variance distribution, the central limit theorem suggests convergence of the average abnormal performance to the normal distribution. Since the current sample of events is sufficiently large we can assume that the average abnormal performance is normally distributed. To verify this assumption a Jarque–Bera (1980) test is conducted. The test is based on the estimated higher moments, i.e. coefficients of skewness and kurtosis of the data over the estimation period.

Since there is specific interest in the timing of abnormal performance, cumulative average abnormalities common for event studies are not applied; instead daily average abnormal performance is measured on and around the event date.

The null hypothesis to be tested is defined as an absence of average abnormal performance on a particular day, i.e. the event, pre- and post-event days. The alternative hypothesis is the existence of an abnormal performance. The test statistics is defined in the following matter:

$$TStat_t = \frac{AAbX_t}{SD(AAbX_t)} \tag{5}$$

Under the assumption of normality, the ratio of the average abnormal performance to its standard variation is distributed as Student-t with degrees of freedom equal to the number of events and can be approximated by standard normal, since the number of events is large.

The variance of average abnormal performance is measured in two different ways. The crude adjustment method of Brown and Warner (1980) accounts for the cross-sectional dependence, but assumes that the event-induced variance is insignificant.

$$SD(AAbX) = \sqrt{\frac{1}{99}\sum_{te=-103}^{-4}(AAbX_t)^2} \tag{6}$$

Cross-sectional dependence is important when event clustering is present. The latter is revealed in our data. Boehmer *et al.* (1991) review other methods and argue that there is a significant increase in the variance associated with the event. The alternative method that accounts for an event-induced variance is an ordinary cross-sectional method:

$$SD(AAbX_t) = \sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N}\left(AbX_{i,t} - AAbX_t\right)^2} \tag{7}$$

However, the latter method ignores cross-sectional dependence. Both methods for variance estimation are compared in the study.

3. Data

The study covers the period June 1997 to March 2003. The sample consists of US traded securities with a volume over 10 million per day and market capitalization over 1 billion US dollars, giving in total 36 stocks from different sectors. The selection of the sample ensures considerable interest and attention of brokerage firm analysts. Information regarding daily opening, closing, high and low price and volume for each security in the sample is obtained from Datastream Advance 4.0 (refer to Appendix A for sample companies' details). The study examines about 2,000 recommendation updates produced by 165 brokerage firms. The data was obtained from Briefing.com, a provider of live market commentary. An upgrade is defined as a change from a less favourable grade to a better, e.g. from 'strong sell' to 'sell' (or better), a downgrade is defined conversely, e.g. from 'strong buy' to 'buy' (or worse). It is often the case that several analysts update their rating regarding the same stock on the same day. When analysts have heterogeneous opinions their updates move in different directions. Those periods are defined as 'analysts' wars' versus 'peace' periods when analysts agree. If there are multiple updates regarding one stock on the same day in one direction, they are treated as one event. The abnormal performance is measured separately for the upgrades and the downgrades. Later, the differences between single and multiple recommendations, as well as 'analysts' wars' versus 'peace' periods are investigated.

4. Estimation Procedure and Results

The data suggests that on average events occur every 2.2 days, which causes event clustering. This may affect distributional assumption of the average abnormal performance and thus, test statistics may be misleading. Bernard (1987) addresses the problem of cross-sectional dependence and concludes that it can cause serious bias in event studies. However, he finds that in the case of daily observations, the cross-correlations are relatively small and thus, do not produce a large bias. The remaining bias is accounted by applying a crude adjustment variance estimator (6).

Further, to determine whether the normality assumption is valid for the average abnormal performance Jarque–Bera (J–B) test is applied. The normality of the average abnormal performance was assessed for each pre-event day over the estimation period of 100 days. The procedure requires serial independence, which is strictly not the case with our data. However, the cross-correlations are relatively small and therefore do not produce a strong bias. Under the null hypothesis of normality the J–B statistic is distributed chi-square with two degrees of freedom (see Appendix B). The J–B statistic for all average abnormal performances, but the downgrade abnormal volatility, appeared insignificant at 5% level. Therefore, we expect complications with inference in the case of the downgrade abnormal volatility.

The time series of average abnormal returns, volatilities and volumes over the period from –30 to 30 days centred on the event date are exhibited in Appendix C. The research focuses on three cases: first, upgrades are compared with downgrades; then volatility and volume in the period of the 'analysts' wars' are compared with the 'peace' periods (both upgrades and downgrades are pulled together for the purpose of such a comparison); and finally, single recommendations (i.e. produced by just one agency) are compared with double and multiple recommendations (i.e. produced by more than one agency) separately for the case of upgrades and downgrades. The estimated abnormal performance, its variance and the test statistics are reported in Appendix D.

A considerable change in the average abnormal return occurs on the event day resulting in a higher absolute jump for downgrades than for upgrades. This is consistent with stylized facts in finance. In the case of downgrades the significant average abnormal return is detected one day prior to the event. It can be an indication of the endogeneity of recommendations and/or market anticipation of the downgrades. The latter can result from information leakages, conflict of interests, and time discrimination, when institutional clients receive information earlier than individual investors. No significant abnormal return is observed after the day of the recommendation update.

The average abnormal volatility is significant one day prior and on the day of the event. This indicates vulnerability of the market in anticipation of the updates. Furthermore, in the case of downgrades, the volatility increases considerably two days before the event, reaches a peak on the day of the event, falls on the subsequent day, maintaining abnormal level for two more days. However, the inference procedure for the downgrade average abnormal volatility is subject to statistical scepticism since the failure of the previously discussed J–B test. The downgrade average abnormal volatility is twice as much as the upgrade volatility. This behaviour is consistent with an established fact in finance (Nelson, 1991). The volatility jumps in our data do not reveal fast mean-reversion.

The behaviour of average abnormal volume is very similar to the behaviour of average abnormal volatility. This is in agreement with the fact that volume can be a good predictor for volatility. Jones *et al.* (1994) argue that volume is a proxy for the number of transaction. The latter translated into fees and commissions can be linked to the profits of brokerage houses. This sheds additional light on the motivation of brokerage houses to provide recommendations and upgrade them regularly. Moreover, by connecting volumes with liquidity we may conclude that recommendations increase market liquidity.

Comparing two methods for the variance estimation a crude adjustment method provides a more conservative estimate than an ordinary cross-section. The former corrects for event clustering and the latter time-varying variance. Nevertheless, the test statistics derived from both methods agree most of the time.

When analysts have heterogeneous beliefs in their recommendations 'analysts' wars' take place in the market. The data reveal levels of volatility and volume approximately twice as high during the 'war' as during the 'peace' period. Since the number of events during 'peace' time is larger than during 'war', the former period's estimates produce less variance. Therefore comparison of the results may not be fully appropriate. Nevertheless, the volume data exhibit reasonably moderate variance for the 'war' estimates, so the results are fully comparable. The 'analysts' wars' trigger heterogeneous beliefs in the market, which create extra vulnerability. The findings are in line with trends in recent literature on heterogeneous beliefs (Shalen, 1993).

The comparison of single and double and multiple recommendations may provide additional insights into the motivation of the herding behaviour of analysts. The data indicate that the absolute values of the average abnormal return is three times higher in the case of double and multiple recommendations than in the case of single ones, the volatility is about twice as high, with an even larger difference in the case of downgrades while the volume is approximately three times higher. The problem with a different number of observations similar to the 'war versus peace' analysis, arises here as well. However, the variance of the estimates is comparable for both types and the above comparisons are statistically correct. Thus, it can be concluded that double and multiple updates produce a much stronger effect on the stock market and it may be fruitful for analysts to exercise some form of collusion to maximize the effect of their announcements. Direct evidence of such collusions has not been established yet.

5. Conclusions

This study has investigated the effect of updates of analysts' recommendations on a sample of large cap US securities and found that analysts have a great impact on stock returns, volatility estimates and volumes.

A 'one day prior to an announcement' effect has been detected in the case of downgrades and can be attributed to some endogeneity of recommendations, information leakages and asymmetries.

The association of volatility with analyst recommendations found in this research can have serious implications for option pricing, and risk management.

The volumes, which are connected with profits of brokerage corporations and market liquidity, showed the phenomenon of clustering for some period prior to and after the event.

The study of 'analysts' wars' versus 'peace' periods revealed interesting implications for the volatility and the volume. It appeared that 'war' periods encouraging heterogeneous beliefs are characterized by increased volatility and volume.

The effect of a single recommendation was compared to that resulting from double and multiple recommendations. It has been shown that double and multiple updates have much more impact on market reaction.

Further analysis is needed to address exogeneity of analysts' recommendations.

Appendix A. Stocks in Sample

Table A.1. Selection criteria: US stock market, Volume > 10 M/day, Market Capitalization > USD 1B

Ticker	Company	Industry	Avg. Vol, M	Mkt Cap, B
AMAT	Applied Materials Inc	Semiconductors	28.15	25.08
AMGN	Amgen Inc	Biotechnology & Drugs	10.62	81.59
AOL	AOL Time Warner Inc	Computer Services	21.21	60.41
BEAS	BEA Systems Inc	Software & Programming	10.29	4.90
BRCM	Broadcom Corp	Semiconductors	10.62	5.28
CSCO	Cisco Systems Inc	Communications Equipment	62.62	108.60
DELL	Dell Computer Corp	Computer Hardware	21.54	75.94
EMC	EMC Corp	Computer Storage Devices	15.18	20.73
EP	El Paso Corp	Natural Gas Utilities	11.59	4.60
F	Ford Motor Co	Auto & Truck Manufacturers	12.73	18.39
GE	General Electric Co	Conglomerates	21.79	290.64
GLW	Corning Inc	Communications Equipment	10.31	6.55
HD	Home Depot Inc	Retail (Home Improvement)	10.84	65.40
HPQ	Hewlett-Packard Co	Computer Peripherals	11.98	50.82
INTC	Intel Corp	Semiconductors	55.55	124.66
JDSU	JDS Uniphase Corp	Communications Equipment	25.06	4.53
JNPR	Juniper Networks	Communications Equipment	11.35	4.20
JPM	JP Morgan Chase & Co	Money Center Banks	10.06	59.78
KLAC	KLA Tencor Corp	Semiconductors	11.42	8.02
LU	Lucent Technologies Inc	Communications Equipment	37.93	7.50
MO	Altria Group Inc	Tobacco	11.44	62.98
MOT	Motorola Inc	Communications Equipment	10.96	18.64
MSFT	Microsoft Corp	Software & Programming	63.18	280.17
NT	Nortel Networks Corp	Communications Equipment	20.04	10.35
NXTL	Nextel Communications Inc	Communications Services	22.81	15.59
ORCL	Oracle Corp	Software & Programming	39.79	63.96
PFE	Pfizer Inc	Major Drugs	18.43	251.53
QCOM	Qualcomm Inc	Communications Equipment	14.70	25.35
SBC	SBC Communications Inc	Communications Services	10.38	79.72
SEBL	Siebel Systems Inc	Software & Programming	10.67	4.73
SUNW	Sun Microsystems Inc	Computer Hardware	48.59	11.98
TXN	Texas Instruments Inc	Semiconductors	10.57	33.36
TYC	Tyco International Ltd	Conglomerates	14.97	33.49
XLNX	Xilinx Inc	Semiconductors	10.87	9.21
XOM	Exxon Mobil Corp	Oil & Gas – Integrated	11.59	241.10
YHOO	Yahoo Inc	Computer Services	11.45	15.03

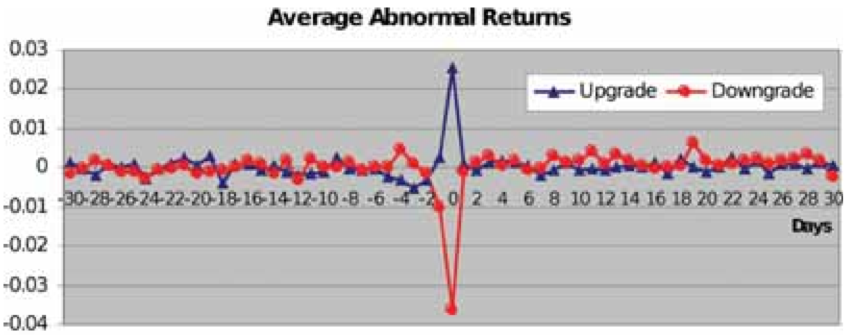
Appendix B. Jarque–Bera Test

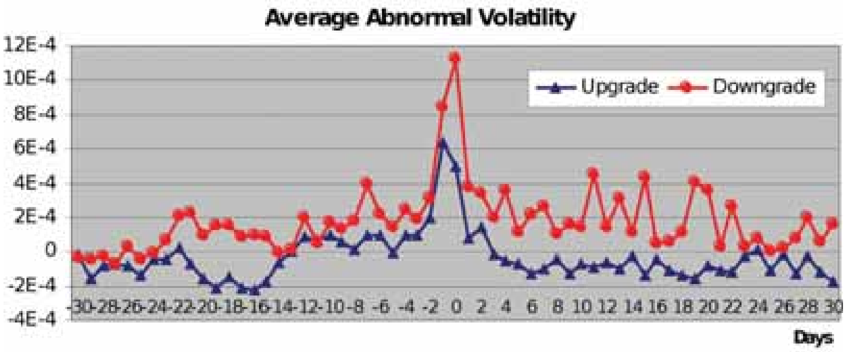
Table B.1. Under the null hypothesis of normality J-B test statistic is Chi square distributed with two degrees of freedom (95% critical value: 5.99)

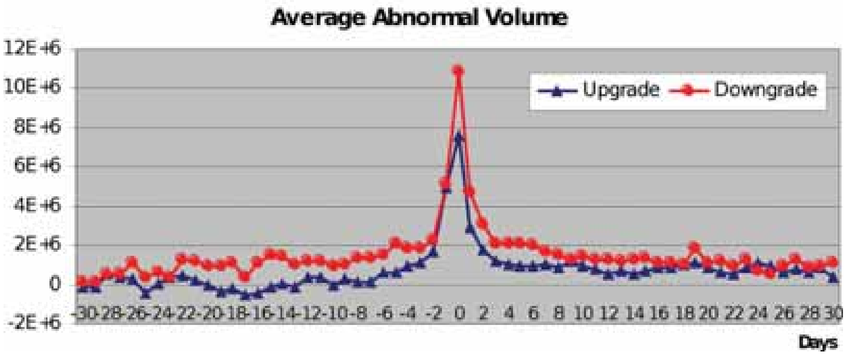
	Up Abnormal returns	Down Abnormal returns	Up Abnormal volatility	Down Abnormal volatility	Up Abnormal volume	Down Abnormal volume
Skew	0.0365	0.1945	0.2505	0.7399	0.3032	0.5147
Kurtosis	−0.4738	0.5154	0.3195	1.0293	−0.0911	−0.5013
J-B	0.9576	1.7374	1.4713	13.5387*	1.5671	5.4629

*Reject H_0 at 5% significance level

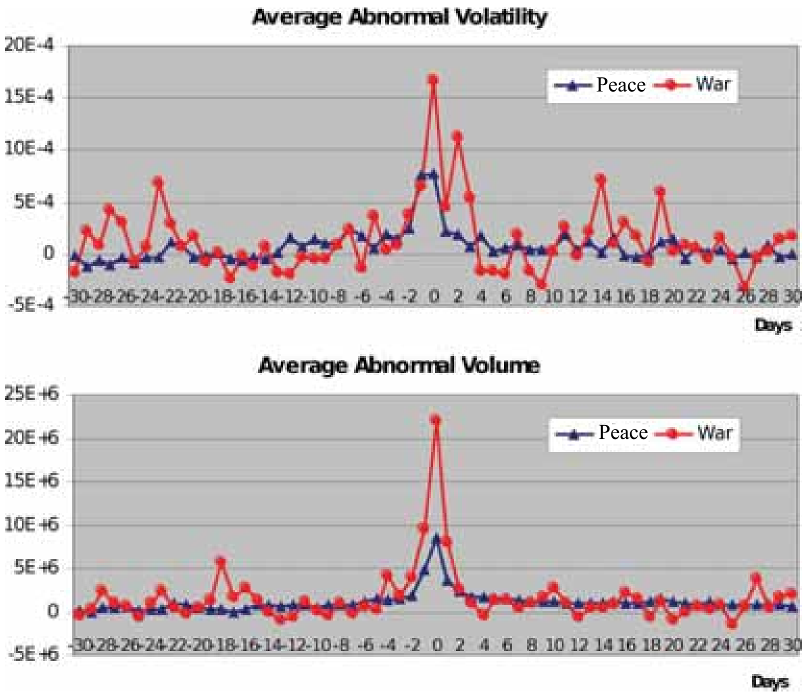
Appendix C. Time Series Centred Around Event Date 0: Upgrades vs. Downgrades



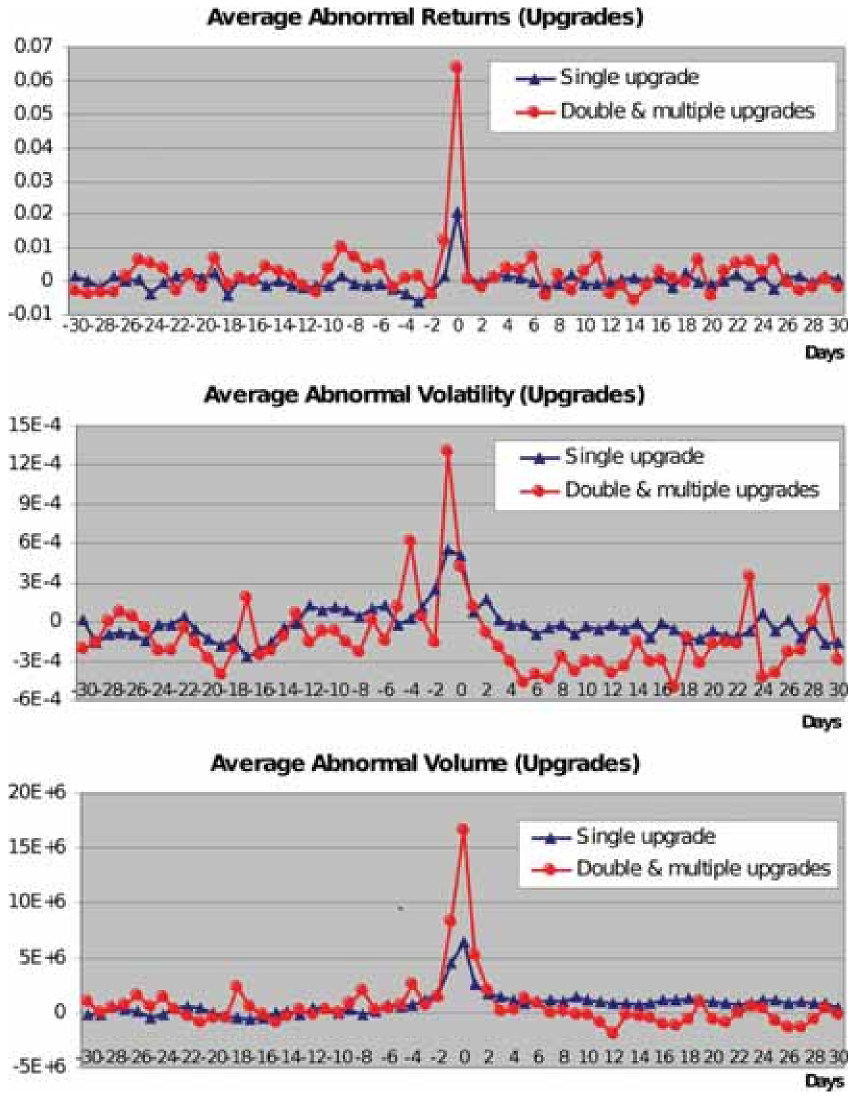




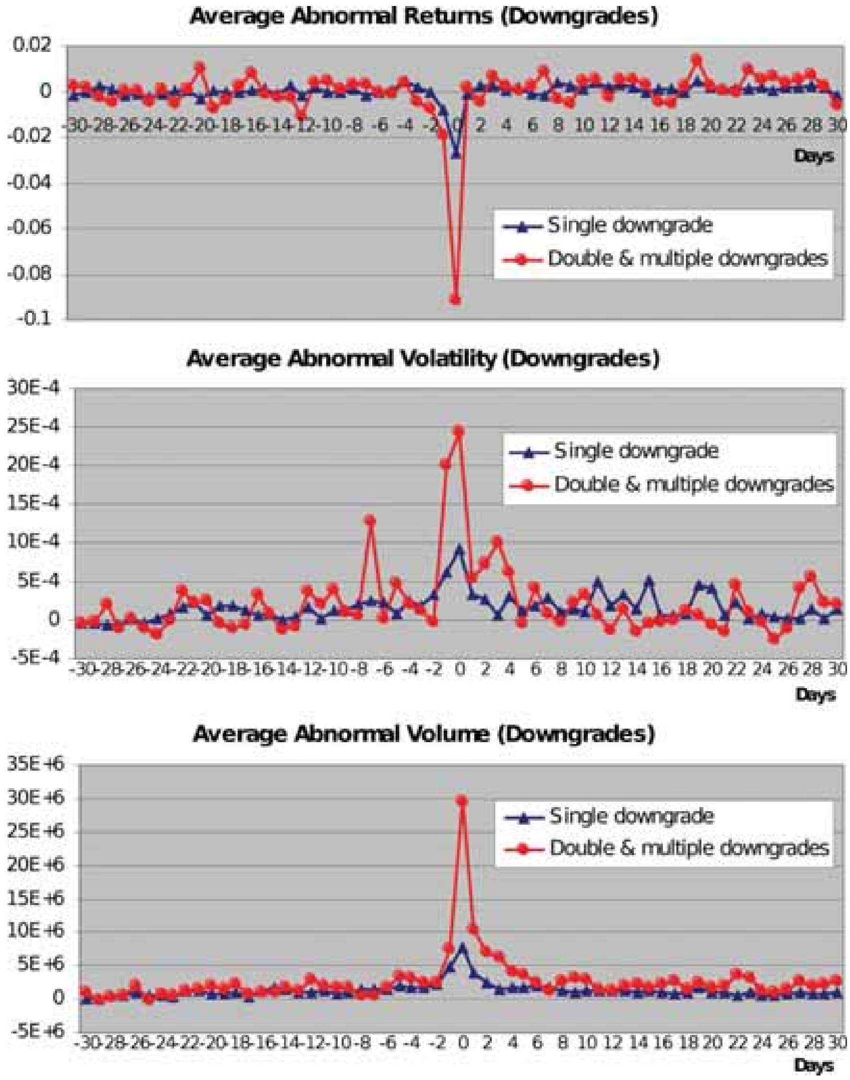
Time Series Centred Around Event Date 0: "Analysts' Wars" vs. "Peace"



Time Series Centred Around Event Date 0: Single vs. Double and Multiple Upgrades



Time Series Centred Around Event Date 0: Single vs. Double and Multiple Downgrades



Appendix D. Estimation Results: Upgrades vs. Downgrades

Report format:

1. Average abormal performance (**bold** if 5% significant for both methods)
2. Standard deviation, ordinary cross-sectional (OCS) methods
3. Test statistics, OCS method (*italic*)
4. Standard deviation, crude adjustment (CA) method
5. Test statistics, CA method (*italic*)
   Ho: No abnormal performance. Test statistics is asympt, standard normal.

Days	−5	−4	−3	−2	−1	0	1	2	3	4	5
Average Abnormal Returns, 10^{-3}											
Upgrade	−2.14	−3.10	**−5.11**	−3.29	2.61	**25.64**	0.86	−0.67	1.44	1.85	1.23
SE, OCS	1.30	1.39	1.42	1.48	1.87	1.89	1.31	1.28	1.32	1.30	1.22
STAT, OCS	*−1.65*	*−2.23*	*−3.61*	*−2.23*	*1.40*	*13.60*	*0.66*	*−0.53*	*1.10*	*1.43*	*1.01*
SE, CA	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78	1.78
STAT, CA	*−1.20*	*−1.74*	*−2.87*	*−1.85*	*1.46*	*14.40*	*0.48*	*−0.38*	*0.81*	*1.04*	*0.69*
Downgrade	−0.02	**4.64**	1.02	−1.49	**−10.23**	**−36.45**	−1.15	1.47	2.91	0.52	1.56
SE, OCS	1.58	1.48	1.57	1.60	1.93	2.27	1.66	1.39	1.50	1.54	1.48
STAT, OCS	*−0.01*	*3.15*	*0.65*	*−0.93*	*−5.31*	*−16.07*	*−0.69*	*1.06*	*1.94*	*0.34*	*1.05*
SE, CA	1.55	1.55	1.55	1.55	1.55	1.55	1.55	1.55	1.55	1.55	1.55
STAT, CA	*−0.01*	*2.99*	*0.66*	*−0.96*	*−6.59*	*−23.46*	*−0.74*	*0.95*	*1.87*	*0.33*	*1.00*
Average Abnormal Volatility, 10^{-4}											
Upgrade	−0.10	0.95	1.00	2.02	**6.43**	**4.95**	0.74	1.39	−0.12	−0.58	−0.76
SE, OCS	0.56	0.78	0.61	0.84	1.18	1.04	0.65	0.88	0.65	0.49	0.55
STAT, OCS	*−0.18*	*1.22*	*1.65*	*2.40*	*5.46*	*4.75*	*1.14*	*1.57*	*−0.18*	*−1.19*	*−1.36*
SE, CA	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14	1.14
STAT, CA	*−0.09*	*0.83*	*0.87*	*1.76*	*5.62*	*4.33*	*0.65*	*1.21*	*−0.10*	*−0.51*	*−0.66*
Downgrade	1.46	**2.48**	1.91	**3.12**	**8.46**	**11.26**	**3.74**	**3.35**	2.03	**3.59**	1.15
SE, OCS	0.60	0.83	0.68	0.96	1.58	1.27	0.74	0.91	0.86	0.97	0.65
STAT, OCS	*2.43*	*2.97*	*2.82*	*3.24*	*5.35*	*8.83*	*5.08*	*3.69*	*2.35*	*3.68*	*1.75*
SE, CA	1.17	1.17	1.17	1.17	1.17	1.17	1.17	1.17	1.17	1.17	1.17
STAT, CA	*1.25*	*2.12*	*1.63*	*2.66*	*7.23*	*9.62*	*3.20*	*2.87*	*1.73*	*3.07*	*0.98*
Average Abnormal Volume, 10^{6}											
Upgrade	0.52	**1.25**	**0.96**	**1.63**	**5.53**	**9.56**	**3.63**	**1.93**	**1.16**	**0.93**	**1.03**
SE, OCS	0.27	0.35	0.35	0.30	0.45	0.52	0.30	0.25	0.37	0.26	0.25
STAT, OCS	*1.92*	*3.54*	*2.76*	*5.52*	*12.20*	*18.40*	*11.91*	*7.64*	*3.12*	*3.57*	*4.06*
SE, CA	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45
STAT, CA	*1.14*	*2.75*	*2.13*	*3.60*	*12.21*	*21.09*	*8.00*	*4.25*	*2.57*	*2.06*	*2.26*
Downgrade	**2.62**	**2.01**	**1.92**	**2.50**	**5.92**	**18.49**	**6.75**	**4.62**	**3.31**	**2.59**	**2.80**
SE, OCS	0.36	0.32	0.31	0.35	0.39	1.06	0.46	0.42	0.33	0.36	0.35
STAT, OCS	*7.26*	*6.34*	*6.20*	*7.24*	*15.14*	*17.40*	*14.54*	*11.07*	*9.90*	*7.27*	*7.91*
SE, CA	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
STAT, CA	*2.78*	*2.12*	*2.03*	*2.65*	*6.27*	*19.57*	*7.14*	*4.89*	*3.51*	*2.74*	*2.96*

Estimation Results: "Analysts' Wars" vs. "Peace"

Days	−5	−4	−3	−2	−1	0	1	2	3	4	5
Average Abnormal Volatility, 10^4											
Peace	0.54	**1.81**	1.50	**2.52**	**7.53**	**7.74**	**2.18**	**1.92**	0.76	**1.74**	0.32
SE, OCS	0.42	0.60	0.48	0.67	1.05	0.84	0.51	0.56	0.52	0.58	0.45
STAT, OCS	*1.30*	*3.02*	*3.13*	*3.77*	*7.21*	*9.26*	*4.25*	*3.45*	*1.46*	*2.99*	*0.71*
SE, CA	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80	0.80
STAT, CA	*0.69*	*2.29*	*1.89*	*3.17*	*9.47*	*9.74*	*2.75*	*2.42*	*0.96*	*2.19*	*0.41*
War	3.64	0.31	0.84	3.77	**6.43**	**16.56**	4.17	11.16	5.13	−1.69	−1.59
SE, OCS	2.94	1.72	1.30	2.81	2.05	6.83	2.35	9.72	6.58	2.01	2.19
STAT, OCS	*1.24*	*0.18*	*0.65*	*1.34*	*3.14*	*2.42*	*1.78*	*1.15*	*0.78*	*−0.84*	*−0.73*
SE, CA	2.63	2.63	2.63	2.63	2.63	2.63	2.63	2.63	2.63	2.63	2.63
STAT, CA	*1.38*	*0.12*	*0.32*	*1.43*	*2.45*	*6.30*	*1.59*	*4.24*	*1.95*	*−0.64*	*−0.60*
Average Abnormal Volume, 10^6											
Peace	**1.44**	**1.29**	**1.49**	**1.88**	**4.80**	**8.58**	**3.62**	**2.45**	**1.73**	**1.67**	**1.52**
SE, OCS	0.24	0.24	0.28	0.26	0.33	0.44	0.29	0.25	0.28	0.26	0.25
STAT, OCS	*5.88*	*5.41*	*5.36*	*7.18*	*14.66*	*19.48*	*12.46*	*9.65*	*6.23*	*6.48*	*6.05*
SE, CA	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49	0.49
STAT, CA	*2.94*	*2.64*	*3.05*	*3.84*	*9.82*	*17.54*	*7.40*	*5.02*	*3.55*	*3.42*	*3.11*
War	0.17	4.14	1.83	**4.00**	**9.41**	**21.79**	**7.65**	2.38	0.84	−0.43	1.26
SE, OCS	1.91	2.21	1.36	1.90	2.41	3.54	1.83	1.58	2.01	1.66	1.42
STAT, OCS	*0.09*	*1.87*	*1.34*	*2.11*	*3.90*	*6.16*	*4.18*	*1.51*	*0.42*	*−0.26*	*0.89*
SE, CA	1.89	1.89	1.89	1.89	1.89	1.89	1.89	1.89	1.89	1.89	1.89
STAT, CA	*0.09*	*2.19*	*0.97*	*2.12*	*4.99*	*11.55*	*4.05*	*1.26*	*0.45*	*−0.23*	*0.66*

Estimation Results: Single vs. Double & Multiple Recommendations

S – Single recommendation
D&M – Double and Multiple recommendations

Days	−5	−4	−3	−2	−1	0	1	2	3	4	5
Average Abnormal Returns, 10^{-3}											
S Up	−2.18	**−3.64**	**−5.96**	**−3.24**	1.39	**20.69**	0.97	−0.49	1.49	1.61	0.95
SE, OCS	1.36	1.45	1.47	1.58	1.95	1.86	1.39	1.39	1.42	1.40	1.30
STAT, OCS	*−1.60*	*−2.51*	*−4.05*	*−2.05*	*0.71*	*11.12*	*0.70*	*−0.35*	*1.05*	*1.15*	*0.73*
D&M Up	−1.77	1.00	1.42	−3.66	**11.97**	**63.59**	0.01	−2.05	1.06	3.79	3.34
SE, OCS	4.19	4.66	4.78	4.12	6.11	7.10	3.85	3.14	3.41	3.35	3.50
STAT, OCS	*−0.42*	*0.22*	*0.30*	*−0.89*	*1.96*	*8.96*	*0.00*	*−0.65*	*0.31*	*1.13*	*0.95*
S Down	0.15	**4.87**	1.59	−0.49	**−8.40**	**−27.29**	−1.34	2.21	2.45	0.45	1.59
SE, OCS	1.73	1.56	1.64	1.73	1.95	2.05	1.78	1.46	1.59	1.60	1.63
STAT, OCS	*0.09*	*3.12*	*0.97*	*−0.29*	*−4.31*	*−13.29*	*−0.75*	*1.52*	*1.54*	*0.28*	*0.97*
D&M Down	−1.08	3.27	−2.37	−7.49	**−21.27**	**−91.39**	−0.05	−2.91	5.68	0.93	1.36
SE, OCS	3.88	4.38	4.83	4.19	6.72	8.83	4.62	4.32	4.44	4.91	3.50
STAT, OCS	*−0.28*	*0.75*	*−0.49*	*−1.79*	*−3.16*	*−10.35*	*−0.01*	*−0.67*	*1.28*	*0.19*	*0.39*
Average Abnormal Volatility, 10^{-4}											
S Up	−0.24	0.29	1.10	2.51	**5.58**	**5.09**	0.71	1.69	0.14	−0.24	−0.24
SE, OCS	0.57	0.63	0.65	0.93	1.11	1.15	0.70	0.99	0.72	0.53	0.61
STAT, OCS	*−0.42*	*0.47*	*1.71*	*2.70*	*5.02*	*4.43*	*1.02*	*1.71*	*0.19*	*−0.46*	*−0.40*
D&M Up	1.08	**6.10**	0.32	−1.62	**13.10**	**4.03**	1.09	−0.87	−1.96	**−3.06**	**−4.58**
SE, OCS	2.04	4.71	1.84	1.62	5.61	2.00	1.78	1.08	1.31	1.11	1.11
STAT, OCS	*0.53*	*1.29*	*0.17*	*−1.00*	*2.34*	*2.01*	*0.61*	*−0.81*	*−1.49*	*−2.74*	*−4.11*
S Down	0.93	**2.56**	**1.86**	**3.41**	**6.33**	**9.15**	**3.37**	**2.72**	0.69	**3.11**	1.34
SE, OCS	0.57	0.88	0.70	1.09	1.20	1.13	0.80	0.80	0.61	1.09	0.71
STAT, OCS	*1.62*	*2.91*	*2.64*	*3.13*	*5.29*	*8.08*	*4.23*	*3.40*	*1.13*	*2.85*	*1.87*
D&M Down	4.63	1.96	2.21	1.40	**21.23**	**23.94**	**6.01**	7.18	**10.06**	6.47	0.04
SE, OCS	2.41	2.48	2.15	1.64	8.38	5.70	1.94	4.19	4.79	1.92	1.65
STAT, OCS	*1.92*	*0.79*	*1.03*	*0.85*	*2.54*	*4.20*	*3.10*	*1.71*	*2.10*	*3.37*	*0.02*
Average Abnormal Volume, 10^{6}											
S Up	**0.63**	**0.77**	**1.20**	**1.76**	**4.54**	**6.41**	**2.60**	**1.73**	**1.36**	**1.08**	**0.88**
SE, OCS	0.30	0.30	0.44	0.35	0.49	0.48	0.34	0.29	0.47	0.32	0.29
STAT, OCS	*2.10*	*2.56*	*2.72*	*5.06*	*9.34*	*13.33*	*7.68*	*6.06*	*2.88*	*3.44*	*3.08*
D&M Up	0.68	2.60	0.68	1.40	**8.26**	**16.58**	**5.17**	**1.91**	0.16	0.26	1.35
SE, OCS	1.06	1.65	0.81	0.95	1.76	1.85	0.92	0.80	0.77	0.70	0.85
STAT, OCS	*0.64*	*1.58*	*0.84*	*1.48*	*4.69*	*8.95*	*5.62*	*2.37*	*0.21*	*0.38*	*1.58*
S Down	**1.86**	**1.67**	**1.77**	**2.21**	**4.71**	**7.75**	**3.81**	**2.47**	**1.46**	**1.78**	**1.78**
SE, OCS	0.38	0.36	0.40	0.43	0.47	0.56	0.48	0.41	0.35	0.43	0.44
STAT, OCS	*4.90*	*4.63*	*4.46*	*5.10*	*9.96*	*13.86*	*7.89*	*5.99*	*4.20*	*4.11*	*4.06*
D&M Down	**3.38**	**3.06**	**2.43**	**2.44**	**7.50**	**29.41**	**10.12**	**6.95**	**6.12**	**4.02**	**3.69**
SE, OCS	1.40	1.15	0.84	0.95	1.17	3.43	1.37	1.39	1.20	1.12	0.93
STAT, OCS	*2.42*	*2.66*	*2.88*	*2.57*	*6.41*	*8.56*	*7.39*	*4.98*	*5.11*	*3.60*	*3.96*

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