Preliminary version

The Availability Heuristic and Investors' Reaction to Company-Specific Events

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Abstract

Contemporary research documents various psychological aspects of economic decision-making. The main goal of our study is to analyze the role of the *availability heuristic* (Tversky and Kahneman, 1973, 1974) in financial markets. The availability heuristic refers to people's tendency to determine the likelihood of an event according to the easiness of recalling similar instances, and, thus, to overweight current information, as opposed to processing all relevant information. We define and test two aspects of the availability heuristic which we dub outcome- and risk-availability. The former deals with the availability of positive and negative investment outcomes, and the latter - with the availability of financial risk. We test the availability effect on investors' reactions to analyst recommendation revisions. Employing daily market returns as a proxy for outcome availability, we find that positive stock price reactions to recommendation upgrades are stronger when accompanied by positive stock market index returns, and negative stock price reactions to recommendation downgrades are stronger when accompanied by negative stock market index returns. The magnitude of the outcome availability effect is negatively correlated with the firms' market capitalization, and positively correlated with stock beta, as well as with historical return volatility. Regarding risk availability, we find that on days of substantial stock market moves, abnormal stock price reactions to upgrades are weaker, and abnormal stock price reactions to downgrades are stronger. Both availability effects remain significant even after controlling for additional company-specific and event-specific factors, including market capitalization, stock beta, historical volatility of stock returns, cumulative excess stock returns over one month preceding the recommendation revision, rating category before the revision, and number of categories changed in the revision.

Keywords: Analyst Recommendation Revisions; Availability Heuristic; Behavioral Finance; Outcome Availability; Risk Availability.

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1. Introduction

Decision-making is an integral part of everyday life. The range of decisions from the viewpoint of their complexity and importance may be enormous. As human beings, when making decisions we often take into consideration our past experience, even when it is hardly relevant for our present and future. Moreover, we are subject to various external influences and may vary our behavior as a function of our contemporaneous feelings and emotions. As a result, our decisions and, consequently, actions often depart from rationality.

In our research, we analyze a well-known category of events whose influence on stock returns is widely documented, namely, analyst recommendation revisions. Analyst recommendations represent an important means of transmitting company-specific information to market investors. It has been widely documented that analyst recommendation upgrades are surrounded by abnormally high stock returns, while the downgrades are accompanied by abnormally low stock returns. These abnormal returns are in the focus of our research, and we attempt to understand how they are affected by investors' psychology.

The main psychological concept we deal with is *availability* (Tversky and Kahneman, 1973, 1974)), one of the heuristics affecting the process of decision-making. The availability heuristic asserts that people estimate frequencies or probabilities by the ease with which related instances or associations could be brought to their minds and, thus, overweight current information, as opposed to processing all relevant information. In the framework of our research, we concentrate on stock investment decisions which are routinely made under conditions of uncertainty. Before making a decision to buy a stock, keep holding it, or sell it, investors should estimate the probabilities of gain and loss outcomes associated with the stock. Analyst recommendation upgrades and downgrades increase the subjective probabilities of the gain and loss outcomes, respectively, as reflected in stock returns. Yet, beyond the direct effect based on the information embedded in the recommendations, there may be additional surrounding factors affecting the valuation.

We employ the contemporaneous stock market returns as a proxy for factors affecting investors' interpretation of the company-specific events.[2] We define and test two aspects of availability, namely, outcome- and risk-availability. With respect to the former aspect, we conjecture that high availability of gain and loss outcomes under financial uncertainty may result in

[2] That is, we presume that either the factors increasing the availability of gain and loss outcomes are also expressed in positive and negative contemporaneous stock market returns, respectively, or that the market tendency itself increases the availability of the respective outcomes. Both schemes would result in the same prediction with respect to the effect of availability as proxied by contemporaneous market returns.

amplified stock price reactions to contemporaneous analyst recommendation upgrades and downgrades, respectively. Therefore, we employ the general market tendency as a proxy for outcome availability, and find that excess market-adjusted stock returns are: (i) higher on the days of recommendation upgrades if the contemporaneous daily index returns are positive, and (ii) lower on the days of recommendation downgrades if the contemporaneous daily index returns are negative. We also document that the magnitude of the effect of outcome availability is negatively correlated with the firms' market capitalization, positively correlated with their stock beta, as well as with their historical return volatility. With respect to the latter availability aspect, risk availability, we find that event-day abnormal stock returns are lower on the days of substantial market returns, when risky investment scenarios are more available to investors. Both availability effects remain significant even after controlling for additional company-specific and event-specific factors, including market capitalization, stock beta, historical volatility of stock returns, cumulative excess stock returns over one month preceding the recommendation revision, rating category before the revision, and number of categories changed in the revision.

The rest of the paper is structured as follows. In Section 2, we review the literature on analyst recommendation revisions and the availability heuristic, presenting both psychological aspects and economic applications. In Section 3, we describe our dataset. Section 4 defines our hypotheses and provides the empirical tests and the results. Section 5 concludes.

2. Literature review

2.1. Analyst recommendations

Security analysts’ stock recommendations have been the focus of a large body of literature in finance. The overall conclusion of this literature seems to be that analyst recommendation revisions contain useful investment information for investors. Stickel (1995) documents the effect of brokerage house recommendation changes on stock prices. Short-term price reaction is found to be a function of the strength of the recommendation; the size of the recommended firm; the contemporaneous earnings forecast revision; the magnitude of the recommendation change; the recommending analyst reputation; and the size of the brokerage house. Womack (1996) analyzes buy and sell recommendations of stocks by security analysts at major U.S. brokerage firms and documents significant systematic discrepancies between pre-recommendation prices and eventual values. The initial return at the time of the recommendation is large, even though few recommendations coincide with new public news or provide previously unavailable facts.

Jegadeesh and Kim (2006) evaluate analyst recommendations in the G7 countries and find that stock prices react significantly to recommendation revisions. Green (2006) finds evidence that early access to stock recommendations provides brokerage firm clients with incremental investment value. After controlling for transaction costs, purchasing (selling short) following upgrades (downgrades) results in positive and significant two-day returns.

An additional aspect analyzed in the context of analyst recommendations deals with the differential ability of security analysts in generating stock recommendations, as measured by the profitability of following these recommendations, and with the subsequent reactions by different groups of investors. Sorescu and Subrahmanyam (2006) analyze some proxies for the ability of analysts making the recommendations, namely, years of experience and reputation of their brokerage houses, and document that revisions by high-ability analysts outperform those by low-ability ones. Mikhail et al. (2004) find that analysts whose recommendation revisions earned the most (least) excess returns continue to outperform (underperform) subsequently. Mikhail et al. (2007) focus on investor-specific responses to recommendation revisions. They find that both large and small traders react to recommendations, however, large investors appear to trade more in response to the amount of information contained in the analyst recommendations.

Some studies analyze the information content of consensus recommendations representing the average recommendation level provided by all the analysts following the respective firm. Barber et al. (2001) document that purchasing (selling short) stocks with the most (least) favorable consensus recommendations, in conjunction with daily portfolio rebalancing and a timely response to recommendation changes, yields annual abnormal gross returns. Jegadeesh et al. (2004) show that naïve adherence to analyst recommendations can be costly, because the level of the consensus recommendation adds value only among stocks with favorable quantitative characteristics, defined as value stocks and positive momentum stocks. Irvine (2003) finds that the market responds more positively to analysts' initiations than to other recommendations.

2.2. Psychological background

In the process of decision-making, people may tend to look for rules that would take into account all the "input data" of a problem and simplify the process of solving it. Such rules are called *heuristics*: techniques of directing attention in learning, discovery or problem-solving. Heuristics often oversimplify the problems and do not result in a fully rational behavior. Following them might result in overestimating the importance of certain facts, while actually ignoring others.

The availability heuristic (Tversky and Kahneman (1973)) refers to the phenomenon of determining the likelihood of an event according to the easiness of recalling similar instances. In other words, the availability heuristic may be described as a rule of thumb, which occurs when people estimate the probability of an outcome based on how easy that outcome is to imagine. As such, vividly described, emotionally-charged possibilities will be perceived as being more likely than those that are harder to picture or difficult to understand. Tversky and Kahneman (1973), carrying a series of psychological experiments, establish that people indeed treat instances that are more easily recalled or scenarios that are easier to imagine as being more likely to occur.

Tversky and Kahneman (1974), provide examples of ways availability may provide practical clues for assessing frequencies and probabilities. They find that familiarity of an object, defined as having personal acquaintance of it, as well as its salience, defined as a state when the features of the object are highlighted, both affect the easiness of recalling the instances related to the object. Furthermore, they argue that "recent occurrences are likely to be relatively more available than earlier experiences" (p. 1127), and, thus, conclude that people assess probabilities by overweighting current information, as opposed to processing all relevant information.

The "recency" aspect of availability heuristic is closely connected to another well-known psychological effect – the effect of *priming*. Priming is an unconscious remembering process, which occurs when a certain stimulus or event contemporaneously increases the availability of (primes) a specific informative category. It may affect information processing and, as a result, also decision making (Baron and Byrne (1997)). Numerous studies demonstrate the occurrence of the priming effect, which is considered an important aspect of social thought (see for example, Higgins et al. (1977), Higgins and King (1981)). Gilad and Kliger (2008) explore the influence of priming on financial decision making, finding that priming manipulations affects investors' risk attitudes and, hence, their investment decisions.

Another aspect affecting availability is vividness or “imagery”. Sherman et al. (2002) give two groups of subjects different (from the point of view of concreteness and easiness to imagine) descriptions of symptoms of a disease, and find that easily-imagined symptoms make people far more inclined to believe that they might get the disease, and Keller et al. (2005) find that subjects who look at photographs showing houses in a flood zone evaluate the flooding risk higher than those who look at neutral photographs.

Kuran and Sunstein (1999) introduce the term “availability cascade” to denote a self-reinforcing process of collective belief formation by which an expressed perception triggers a chain reaction that gives the perception increasing plausibility through its rising availability in public discourse. Mullainathan (2002) develops a model of memory limitations based on two psychological concepts that are related to the availability heuristic: (i) “rehearsal”, suggesting that remembering an event once makes it easier to remember again, and (ii) “associativeness”, asserting that current events can trigger recollection of past events with similar aspects.

2.3. Economic applications of the availability heuristic

A number of papers discuss the influence of the availability heuristic on market investors. Shiller (1998) argues that investors' attention to investment categories (e.g., stocks versus bonds or real estate; investing abroad versus investing at home) may be affected by alternating waves of public attention or inattention. Similarly, Barber and Odean (2007) find that when choosing which stock to buy, investors tend to consider only those stocks that have recently caught their attention (stocks in the news, stocks experiencing high abnormal trading volume, stocks with extreme one day returns). This pattern leads to a bias, especially pronounced for individual investors who are net buyers on high-attention days.

Daniel et al. (2002) conclude that investors and analysts are on average too credulous, that is, when examining an informative event or a value indicator, they do not discount adequately for the incentives of others to manipulate this signal. Credulity may be explained by limited attention and the fact that availability of a stimulus causes it to be weighed more heavily. Frieder (2003) finds that stock traders seek to buy after large positive earnings surprises and sell after large negative earnings surprises, and explains this tendency by the availability heuristic, assuming that the salience of an earnings surprise increases in its magnitude. Chiodo et al. (2003) construct a simple model of belief formation based on the assumption that it is easier for people to recall information which has recently arrived, and respectively, investors overreact to new information. They analyze some economic phenomena, for example, that stocks with very high levels of press coverage underperform in the subsequent two years, and provide heuristics-based explanations.

The availability heuristic is also found to influence the behavior of market analysts. Ganzach (2001) brings support for a model in which analysts base their judgments of risk and return for unfamiliar stocks upon a global attitude. If stocks are perceived as good, they are judged to have high return and low risk, whereas if they are perceived as bad, they are judged to be low in return and high in risk. Lee et al. (2005) discuss the "recency bias", which is the tendency of people to make judgments about the likelihood of events based on their recent experience. They find that analysts' forecasts of firms' long-term growth in earnings per share tend to be relatively optimistic when the economy is expanding and relatively pessimistic when the economy is contracting. This finding is consistent with the availability heuristic, indicating that forecasters overweight current state of the economy in making long-term growth predictions. The authors state that this result is over and above any adaptive forecasting behavior exhibited by analysts that would take into account systematic characteristics of past growth behavior.

A body of papers documents a number of economic phenomena that seem to be in line with the concept of availability. Jarell and Peltzman (1985) study the effect of drug and auto recalls on the wealth of shareholders. They not only document negative effects of product recalls on the recalling company's stock prices, but also find substantial losses for its competitors. They suggest that a current recall makes the risk of buying a faulty product of the same class more available and holds the consumers back from buying such products, implying negative influence on the whole industry. Shelor et al. (1992) find that the California earthquake of 1989 resulted in a significantly positive stock price response for insurance firms. Investors' expectations of higher demand for insurance apparently more than offset the potential earthquake losses. Thus, investors implicitly account for the fact that following an earthquake people overestimate the probability that they will need earthquake insurance. Bosch et al. (1998) estimate the effects of air crashes on the crash airline and its competitors and document that there exists switching effect from crash to non-crash airlines. Yet, in line with our discussion and, in fact, similarly to Jarell and Peltzman (1985), they find a negative effect on the firm value of competitors. This suggests that consumers and/or insurers may be concerned about elements of the commercial air travel system that are involved in the joint production of air safety.

3. Data description

The main data source for our work is the dataset of analyst recommendation revisions for NYSE-listed companies. For the empirical analysis, we take all the companies that were listed on NYSE at the end of 2006. Information on the characteristics of the recommendation revisions, as well as the historical stock price and trading volume are extracted from www.finance.yahoo.com. For each firm, we take the latest upgrade and downgrade, provided: (i) they took place in the period 2001 to 2006; (ii) they are not accompanied by other analyst recommendation revisions within a two trading days window; and (iii) there are historical trading data for at least 251 trading days before the earliest of the two analyst recommendation revisions.

This sampling rule yields 1373 firms, and 2746 analyst recommendation revisions. Table 1 provides basic descriptive statistics of the working sample, by sectors of the economy.[3] Firms' market capitalization ranges from 38.7 to 2,701,406 millions of dollars with a standard deviation of 119,636. Market Model beta estimated over days -251 to -2 relative to the event day varies from 0.05 to 3.23, and the standard deviation of daily stock returns over the same period – from 0.63 to 11.50 percent, with standard deviations of 0.48 and 0.78, respectively[4].

Table 2 classifies the analyst recommendation revisions in our working sample, by rating categories before the revision (Panel A), by the number of categories changed in the revision (Panel B), and by calendar years (Panel C). The recommendations are coded by a five level descending scale[5]. For the vast majority of analyst recommendation revisions in our working sample, only one rating category is changed. Due to the sampling rule, most of the recommendation revisions are relatively recent.

Table 3 presents basic descriptive statistics on the number of events simultaneously taking place within our sample. Overall, 1373 recommendation upgrades (downgrades) are distributed over 510 (511) different trading days and the corresponding number of days rapidly decreases with the number of events per day.

4. Testable hypotheses and results

In this paper, we wish to shed light on the impact of the availability heuristic on the process of decision-making by market investors. Specifically, we aim at testing whether availability affects investors' reactions to analysts' recommendation revisions, reflected in the market-adjusted excess stock returns on the event days. We analyze two aspects of the availability heuristic, namely, outcome- and risk-availability.

4.1. The proxy for outcome availability

In our everyday life, in general, and in the stock market trading, in particular, there exists a wide range of social, economic, political, and environmental factors affecting people's perceptions and, therefore, the availability of different outcomes. On days when positive and negative

[3] For each recommendation revision, firm's market capitalization is registered as the market value of the firm's stocks outstanding at the end of the fiscal year preceding the revision.
[4] Daily historical standard deviations are calculated from the daily stock returns over the year preceding the recommendation revision.
[5] The category 1 corresponds to Strong Buy, 2 is Buy, 3 is Hold, 4 is Sell, and 5 is Strong Sell.

investment outcomes are highly available, it is easier for the investors to imagine scenarios leading to gains and losses, respectively. So, the information content of recommendation upgrades and downgrades, respectively, is perceived more saliently, resulting in amplified stock price reactions.

We employ the daily index returns around recommendation revisions as a proxy for the contemporaneous availability of the respective outcomes, which may be created in two ways:

- On the days when certain factors cause, for example, a positive market index return, investors may react more strongly to recommendation upgrades, as they are made available by the factors above.
- On the days when the market index rises for other reasons, the index increase itself enhances the availability of positive investment scenarios, which results in stronger positive price reactions to recommendation upgrades.

Acting together or separately, both schemes result in the same prediction that stock price reactions to recommendation revisions will be amplified on the days when the direction of change in the stock market index corresponds to the direction of the revision. Thus, by testing for stock price reactions to recommendation revisions conditioned on the sign of index returns, we are able to identify the effect of outcome availability on the perception of company-specific events by the investors.

4.2. Hypothesis formulation and general results

We define the announcement day of each recommendation revision as day 0. Measuring the daily market returns (MRs) by the NYSE Composite Index, we calculate abnormal returns (ARs) for each event (recommendation revision) *i*, using Market Model Adjusted Returns (MMAR), and (ii) Market Adjusted Returns (MAR) – return differences from the market index. Table 4 reports the average abnormal stock returns for the MMAR benchmark around recommendation revisions and their statistical significance.[6] Figures 1 and 2 depict the cumulative average daily ARs over a period starting one month before and ending two days after the recommendation upgrades and downgrades, respectively. The Table and the Figures contain a number of important results. First of all, interestingly, ARs for the period (-30;-2) have significantly opposite direction to that of the subsequent recommendation revisions. A possible reason for this may be that, on the one hand, at least some of the stocks are upgraded, because analysts consider them to be underestimated after a

[6] We also perform the analysis with Market Adjusted Returns (MAR), i.e., return differences from the market index, and obtain similar results. These results are available on request from the authors.

period of negative ARs, and on the other hand, at least some of the stocks are downgraded, because analysts consider them to be overestimated after a period of positive ARs. Second, the stock price effect of the recommendation revisions is most pronounced for day 0 and is also manifested on day -1. Lastly, there are significant negative ARs on days 1 and 2 following the downgrades, but no significant daily return evidence following the upgrades. Therefore, in addition to employing the event day (day 0) ARs for testing the outcome availability effect, we employ day -1 ARs, as well. We therefore hypothesize as follows:

H_0 : Stock returns are not affected by the availability of positive or negative investment outcomes.

H_1 (upgrades): ARs around upgrades are higher, the more available are positive investment outcomes, as reflected by positive contemporaneous MRs.

H_1 (downgrades): ARs around downgrades are lower, the more available are negative investment outcomes, as reflected by negative contemporaneous MRs.

Table 5 presents the average ARs on days -1 and 0, separately for the cases when the contemporaneous MRs (MR_{-1} and MR_0) are positive and negative, the respective differences, and their statistical significance.[7] The results provide strong support for the existence of the outcome availability effect on the ARs related to the analyst recommendation revisions. All the estimated differences are positive and highly significant, meaning that event-driven ARs are higher for upgrades if the contemporaneous daily MRs are positive, and lower for downgrades if the contemporaneous daily MRs are negative.[8] We note also that the availability-driven AR differences are larger on day 0 than on day -1, and for downgrades than for upgrades.[9]

4.3. Outcome availability effect within different stock groups

In this Subsection, we analyze the magnitude of the outcome availability effect by size (market capitalization), stock beta, and historical volatility.[10] The motivation for this analysis is

[7] There were no days with zero market return.

[8] Conditioning event-driven ARs on the sign of the previous day's MR does not yield significant differences between the groups (the results are available on request from the authors). Thus, only the contemporaneous direction of change in the value of stock market index affects the availability of company-specific news of the respective direction.

[9] Though the potential problem of clustering in event dates within our sample looks mild (see Table 3), we have performed a robustness check for the results reported in Tables 5 to 8, based on the alternative method of variance estimation as described by Brown and Warner (1985). To wit, we estimated the standard deviations based on portfolio returns. The results we have obtained (available on request from the authors) are qualitatively similar.

[10] We have also performed the tests separately for each of the sectors reported in Table 1, as well as for each initial rating category. Our findings, available upon request from the authors, apply to the partitioned analysis as well.

based on the findings by Baker and Wurgler (2006), who argue that stocks of low capitalization, growth, and highly volatile stocks are especially likely to be disproportionately sensitive to broad waves of investor sentiment.

First of all, we analyze the outcome availability effect jointly by firm size and beta. Tables 6 and 7 exhibit the results for upgrades and downgrades, respectively. The Tables show the average ARs on days of positive and negative MRs, and their corresponding differences, representing the measure of the outcome availability effect, for day 0, according to a 3x3 partition of the sample by market capitalization and beta, using cutoff points splitting the sample of recommendation revisions into three roughly equal parts by each dimension. Consistently with Baker and Wurgler (2006), as reflected by the rightmost columns and the bottom rows of the Tables, the effect of outcome availability tends to decrease with market capitalization and increase with stock beta. To wit, the prices of low market capitalization stocks and stocks characterized by higher sensitivity to market fluctuations are more affected by the availability heuristic, possibly due to the reduced amount of information on these stocks. Note also that the stock price reactions to recommendation revisions are stronger for lower capitalization and higher beta stocks. Lastly, eyeballing the tables' columns and rows, we note that the results for market capitalization and beta tend to hold also under the ceteris paribus requirement.[11]

Table 8 presents the results for the magnitude of the outcome availability by the historical stock volatility. The Table displays ARs and AR differences for days -1 and 0, according to the division of the sample in three equal-size groups by the standard deviation of stock returns over the estimation period (days -251 to -2). The results show that, in line with Baker and Wurgler (2006), the higher the historical stock volatility, the stronger the outcome availability effect on event-driven ARs.

4.4. Multifactor analysis

Having detected the outcome availability effect, we henceforth check its persistence controlling for additional firm-specific and event-specific factors. To do so, we run the following regressions, separately for days -1 and 0, as well as for upgrades and downgrades:

[11] The results for day -1 (not reported here and available on request from the authors) are qualitatively similar.

$$AR_{it} = \gamma_1 MR\_dum_{it} + \gamma_2 MCap_i + \gamma_3 beta_i + \gamma_4 SR\_volat_i + \gamma_5 Magnitude_i + \gamma_6 AR\_30\_2_i + \sum_{s=j}^{j+3} \varphi_s from_{si} + \varepsilon_{it} \quad (1)$$

where: MR_dum_{it} is the dummy variable, taking the value 1 if the market return corresponding to day t for event i is positive, and 0 otherwise[12], $MCap_i$ is the natural logarithm of the firm's market capitalization corresponding to event i, normalized in the cross-section, $beta_i$ is the estimated CAPM beta for event i, normalized in the cross-section, SR_volat_i is the standard deviation of stock returns over the days -251 to -2 corresponding to event i, normalized in the cross-section, $Magnitude_i$ is the number of categories changed in the revision, $AR\_30\_2_i$ is the cumulative abnormal return over the days -30 to -2 corresponding to event i, normalized in the cross-section, and $from_{si}$ are the dummy variables, taking the value 1 if the initial rating category (according to the numerical scale) before recommendation revision is s (with j equal to 1 for downgrades and 2 for upgrades, to span all possible recommendation revisions within each regression).

Table 9 presents results of the four regressions.

- Regression coefficients on *MR_dum* are positive and highly significant. That is, the effect of outcome availability on investors' reactions to news remains significant even after controlling for additional factors affecting the ARs.
- Investors' reactions to recommendation revisions on day 0 are significantly stronger for small firms. That is, according to the signs of the coefficients on *MCap*, for low capitalization firms, positive ARs following upgrades are higher, and negative ARs following downgrades are lower.
- Controlling for all the variables appearing in the regression, the hypothesis that the magnitude of the outcome availability effect is independent of the stock CAPM betas cannot be rejected.
- Investors' reactions to recommendation revisions are significantly stronger for more volatile stocks. That is, for the stocks with higher historical volatility of returns, positive ARs following upgrades are higher, and negative ARs following downgrades are lower.

[12] Alternatively, for Day 0, we have run regression (1) with actual levels of market returns split in two categories, using two variables to account for positive and negative market movements, instead of *MR_dum*. Coefficient estimates for the negative market returns are positive and highly significant, as they comprise two effects acting in the same direction: the outcome availability effect and the risk availability effect (see description in the sequel). Coefficient estimates for the positive market returns are non-significant, as in this case, the two effects act in the opposite directions. The results are available on request from the authors.

- The evidence on the effect of *Magnitude* on the event-driven ARs is mixed. Nevertheless, including *Magnitude* in the regression assures that the effect of outcome availability on investors' reactions to news remains significant even after controlling for the number of rating categories changed.[13]

4.5. Further empirical examination

Cumulative return analysis

Having analyzed the outcome availability effect on day -1 and day 0 ARs, we now wish to check if the cumulative stock price reaction to recommendation revisions over days -1 and 0 depends on the sign of the cumulative MRs over the same event period. Table 10 reports the cumulative average ARs over days -1 and 0, by the sign of the contemporaneous cumulative MRs (MR_{-1_0}). The results represent additional evidence for the effect of outcome availability on event-driven stock returns, as the cumulative abnormal stock price reactions to upgrades are significantly stronger when the contemporaneous cumulative MRs are positive, and the cumulative abnormal stock price reactions to downgrades are significantly stronger when the contemporaneous cumulative MRs are negative. Also, as in the case of daily returns, the effect of outcome availability on cumulative event-day ARs is stronger for downgrades.[14]

Trading volume analysis

An additional aspect of event-related trading behavior that may be affected by the outcome availability is the trading volume.

Trading volume may reflect heterogeneity in investors' expectations (Copeland (1976), Pfleiderer (1984), and Varian (1985)). Karpoff (1986) demonstrates that trading volume results from dispersion in prior expectations and idiosyncratic interpretations of information events. He also shows that the increase in trading volume is positively correlated with the information

[13] Though the potential problem of clustering in event dates within our sample looks mild (see Table 3), we have performed a robustness check for the results reported in Tables 9, 12, 13, 15, and 17. Because of our sample's characteristics, we could not employ the multi-stage regression described in Fama and MacBeth (1973), and thus, for each trading day in our sample, we have randomly chosen one upgrade and one downgrade revision (maximum of two revisions per day, if available, and overall, 510 upgrades and 511 downgrades). The results we have obtained (available on request from the authors) are qualitatively similar.

[14] We have also repeated the regression analysis reported in subsection 4.4 on the cumulative event-days ARs. The effect of contemporaneous MRs on stock price reactions to recommendation revisions remains highly significant. The regression results are available on request from the authors.

"surprise". According to Karpoff (1987)[15], if a "surprise" is followed by stock price revision in the direction corresponding to the quality of the "surprise", then the contemporaneous trading volume is higher, the greater the absolute value of the price change. Kim and Verrecchia (1991) continuing Karpoff's line of research, define a measure of market's information asymmetry as a ratio of volume to the absolute value of price change. Furthermore, they argue that volume may increase either with the absolute value of stock returns, reflecting the average changes in investors' expectations, or following an increase in information asymmetry.

We normalize the abnormal trading volume in the time series, that is, calculate:

$$ABVOL_i = \frac{Vol_i - AVol_i}{STDVol_i} \quad (2)$$

where: *Voli* is event *i*'s trading volume on day 0 , *AVoli* is the average trading volume over the days -251 to -2, and *STDVoli* is the standard deviation of the trading volume over the days -251 to -2 corresponding to event *i*.

Following Karpoff (1986, 1987) and Kim and Verrecchia (1991), we expect that abnormal trading volume associated with recommendation revisions will be higher for both upgrades and downgrades on the days when the quality of news corresponds to the sign of contemporaneous market returns.

The results in Table 11 support our surmise. The average event-day abnormal volumes following upgrades taking place on the days of positive market returns equal 1.91, compared to 1.55 on the days of negative market returns, and the average event-day abnormal volumes following downgrades taking place on the days of negative market returns equal 2.13, compared to 1.50 on the days of positive market returns. The abnormal volume differences are significant. Thus, though the information asymmetry is not affected by the outcome availability, the latter makes an event more salient, that is, increases its "surprise" component, and leads to stronger average changes in investors' expectations, which results in increased trading volume.

To control for other factors potentially affecting investors' trading behavior, we run the following regressions for upgrades and downgrades:

[15] Karpoff (1987) surveys a large amount of empirical studies documenting that the correlation between trading volume and absolute value of stock price change is positive, for example: Westerfield (1977), Wood et al. (1985), Jain and Joh (1986).

$$ABVOL_i = \gamma_1 MR\_dum0_i + \gamma_2 MCap_i + \gamma_3 beta_i + \gamma_4 SR\_volat_i + \gamma_5 Magnitude_i + \gamma_6 AR\_30\_2_i + \sum_{s=j}^{j+3} \varphi_s from_{si} + \varepsilon_i \qquad (3)$$ [16]

where: *MR_dum0i* is the dummy variable, taking the value 1 if the day-0 market return corresponding to event *i* is positive, and 0 otherwise.

Table 12 reports the regression results.

- Regression coefficients on *MR_dum0* are significant and in the hypothesized direction. To wit, the previously obtained results remain valid even after controlling for additional factors affecting the trading volume. The trading volume differences we document suggest that outcome availability may affect investors' beliefs and expectations with respect to future stock price behavior.
- The trading volume is significantly higher for low capitalization firms. That is, the volume reaction, as well as the price reaction to news is stronger for small firms.

4.6. Risk availability

In this Subsection, we concentrate on the effect of availability on investors' reactions to financial risk. Erb et al. (2002) demonstrate that priming affects people's risk preferences, and that judgments that go against the prime are made with less confidence. Furthermore, Gilad and Kliger (2008) establish that investors' awareness of financial risk, as well as their risk attitude, might be affected by environmental factors. Finally, numerous studies (for example, Slovic et al. (1991), Alhakami and Slovic (1994), McDaniels et al. (1997)) document negative correlation between perceived risks and benefits.

We expect that contemporaneous volatility of stock market index primes risky scenarios, or in other words, creates risk availability. Furthermore, we suggest that on days, when risky scenarios are made available to investors or, alternatively, when investors' risk aversion is increased, they treat the "uncertainty ingredient" of any recommendation revision with more precaution, which results in lower stock returns around the revision. So, on such "risky" days, the positive price

[16] Alternatively, for Day 0, we have run regression (3) with actual levels of market returns split in two categories, using two variables to account for positive and negative market movements, instead of *MR_dum*. Coefficient estimates for the negative market returns are highly significant with their signs corresponding to those of *MR_dum* in Table 12. These estimates comprise two effects acting in the same direction: the outcome availability effect and the risk availability effect (see description in the sequel). Coefficient estimates for the positive market returns are non-significant, as in this case, the two effects act in the opposite directions. The results are available on request from the authors.

reactions to upgrades should be reduced, while the negative price reactions to downgrades should be amplified.

Similarly to Fabozzi and Francis (1977), we define the days of substantial changes in stock market index as the days when the absolute value of market return was larger than half standard deviation of the market's returns measured over the total sampling period (2001-2006). In our sample, we have 1111 recommendation revisions taking place on the days of substantial MRs, of which 630 on the days of substantially positive returns and 481 on the days of substantially negative returns. We hypothesize the following:

H_0 : Stock returns are not affected by the availability of risky investment outcomes.

H_1 : ARs around both upgrades and downgrades are lower, the more available are risky investment outcomes, as reflected by substantial stock market moves.

We analyze the effect of risk availability on event-driven ARs on day 0, which incorporate the largest part of stock price reaction to events, controlling for the effect of outcome availability. For day 0, and separately for upgrades and downgrades, we run the following cross-sectional regressions:

$$AR0_i = \gamma_0 + \gamma_1 MR\_dum0_i + \gamma_2 Subret_i + \varepsilon_i \quad (4)$$

where: $Subret_i$ is the dummy variable, taking the value 1 if the absolute value of the day-0 MR corresponding to event *i* exceeds half standard deviation of the MRs over the sample period, and 0 otherwise.

Table 13 reports the regression coefficient estimates and their respective levels of significance. The results support our hypotheses. On the days of substantial market moves, event-driven positive stock price reactions following recommendation upgrades are weaker, and event-driven negative stock price reactions following recommendation downgrades are stronger. Thus, the risk availability, as reflected by the contemporaneous stock market volatility, affects event-day ARs. Moreover, we note that the outcome availability effect remains significant when controlling for the effect of risk availability. That is: (i) After controlling for the substantial stock market moves, the contemporaneous rises in the market index increase investors' positive reactions to upgrades, and the contemporaneous declines in the market index increase investors' negative reactions to downgrades; (ii) After controlling for the direction of change in the market index, substantial contemporaneous market moves decrease investors' positive reactions to upgrades, and increase investors' negative reactions to downgrades.

Now, having tested for the combined effect of two kinds of availability, we are able to separately test for the effect of substantially positive and negative MRs on investors' perception of the recommendation revisions. We perform such test by partitioning our sample of events by the direction and the magnitude of the contemporaneous MRs. Table 14 reports average day-0 ARs on this 2x2 sample partition, and the respective AR differences. The Table reveals stronger negative effect of substantially positive contemporaneous MRs on the event-driven ARs following upgrades, and stronger negative effect of substantially negative contemporaneous MRs on the event-driven ARs following downgrades. This result may be possibly explained in the following way:

- Positive abnormal stock price reactions to the recommendation upgrades increase when the latter are available for the investors, as reflected by positive contemporaneous MRs. In this situation, if MRs are substantially positive, this decreases the availability of positive outcomes, and subsequently, ARs. On the other hand, negative, including substantially negative contemporaneous MRs do not affect the availability of positive investment outcomes.
- Negative abnormal stock price reactions to the recommendation downgrades increase when the latter are available for the investors, as reflected by negative contemporaneous MRs. In this situation, if MRs are substantially negative, this increases the availability of negative outcomes, and still further decreases ARs. On the other hand, positive, including substantially positive contemporaneous MRs do not affect the availability of negative investment outcomes.

Furthermore, we perform a combined analysis of the effect of outcome and risk availability, after controlling for other factors affecting the event-driven ARs. For day 0, and separately for upgrades and downgrades, we run the following regressions:

$$AR0_i = \gamma_1 MR\_dum0_i + \gamma_2 Subret_i + \gamma_3 MCap_i + \gamma_4 beta_i + \gamma_5 SR\_volat_i + \gamma_6 Magnitude_i + \gamma_7 AR\_30\_2_i + \sum_{s=j}^{j+3} \varphi_s from_{si} + \varepsilon_i \qquad (5)$$

Table 15 presents the regression results. The estimates of *MR_dum0* remain highly significant in this specification, as well. The effect of risk availability on event-driven ARs remains negative, yet, significant only for upgrades.

Effect of risk availability on abnormal trading volumes

Finally in this Subsection, we analyze the effect of risk availability on the event-driven abnormal trading volumes. In Table 16, we report the average day-0 abnormal volumes, for both upgrades and downgrades, on the days of substantial and non-substantial MRs, and the respective volume differences. As implied by Panel B of the Table, day-0 abnormal volumes following downgrades are significantly higher on the days of substantial MRs, while the opposite result for the upgrades is marginally significant. So, we may once again suggest that substantial contemporaneous MRs increase the availability of risky, and undesirable, scenarios.

Now, similarly to the analysis of the outcome availability, we perform the regression analysis of the effect of risk availability on event-day ARs, controlling for additional relevant factors. For upgrades and downgrades, we run the following regressions:

$$ABVOL_i = \gamma_1 Subret_i + \gamma_2 MCap_i + \gamma_3 beta_i + \gamma_4 SR\_volat_i + \gamma_5 Magnitude_i + \gamma_6 AR\_30\_2_i + \sum_{s=j}^{j+3} \varphi_s from_{si} + \varepsilon_i \qquad (6)$$

Table 17 reports the regression results and demonstrates that the effect of risk availability remains significant in the multifactor regression.

5. Concluding remarks

Our paper explored the role of the availability heuristic in financial decision making. In particular, we analyzed its effect on investors' reactions to analyst recommendation revisions. We hypothesized that the availability of positive and negative investment outcomes under financial uncertainty may influence investors' reactions to these events. Assuming that the outcome availability is reflected by contemporaneous market returns, we employed the sign of the market index return as a proxy and tested its effect on stock price reactions to recommendation revisions.

The results of the empirical analysis supported our hypothesis. We documented that for both recommendation upgrades and downgrades, abnormal event-days stock returns were significantly higher if the contemporaneous return on the composite market index was positive. We also found that the outcome availability effect on the stock returns remained significant after controlling for additional company-specific and event-specific factors, including market capitalization, stock beta, historical volatility of stock returns, cumulative excess stock returns over one month preceding the recommendation revision, rating category before the revision, and number of categories changed in the revision. The outcome availability effect was of higher magnitude for low capitalization firms, high beta stocks, and stocks with higher volatility of historical returns, suggesting that the prices of low market capitalization stocks and stocks characterized by higher sensitivity to market fluctuations are more affected by the availability heuristic, possibly due to the reduced amount of information on these stocks.

Furthermore, we documented the outcome availability effect on the stocks' trading volumes. The event-day volumes associated with upgrades and downgrades were significantly higher on days of market rise and decline, respectively. This result also persisted after controlling for additional factors affecting event-day abnormal trading volumes.

Finally, controlling for the sign of contemporaneous market returns and other firm-specific and event-specific factors, we found that on the days of substantial stock market moves abnormal stock price reactions to upgrades were weaker, and abnormal stock price reactions to downgrades were stronger. We suggested that this finding may be explained by risky investment scenarios, psychologically associated with fewer benefits, are made available to investors on such days. Moreover, the negative effect of substantially positive contemporaneous market returns on the event-driven abnormal returns was stronger following upgrades, while the negative effect of substantially negative contemporaneous market returns on the event-driven abnormal returns was stronger following downgrades. This may mean that the availability of company-specific news was not affected on the days of the opposite-sign contemporaneous market returns. We also documented that on the days of substantial MRs, day-0 abnormal volumes following upgrades were significantly lower, and day-0 abnormal volumes following downgrades were significantly higher.

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Tables and Figures

Table 1: Descriptive statistics for the firms making up the working sample

Sector	Number of firms	Market Capitalization, $ millions				Market Model beta				St. Dev. of historical stock returns, percent			
		Avg	StDev	Max	Min	Avg	StDev	Max	Min	Avg	StDev	Max	Min
1. Basic materials	187	36,498	219,538	2,696,471	59.0	1.62	0.53	3.23	0.14	2.34	0.65	5.71	0.99
2. Conglomerates	9	53,654	103,589	334,175	1,722.2	1.01	0.25	1.44	0.59	1.18	0.22	1.62	0.83
3. Consumer goods	173	11,434	34,861	353,027	91.8	0.97	0.40	2.21	0.20	1.86	0.77	4.99	0.70
4. Financial	285	23,149	168,977	2,701,406	67.6	0.94	0.32	1.98	0.09	1.44	0.50	4.32	0.63
5. Healthcare	92	18,798	33,718	179,607	143.7	0.81	0.30	1.82	0.22	2.00	1.22	11.50	0.77
6. Industrial goods	134	7,880	24,721	231,761	76.9	1.34	0.45	2.94	0.26	2.01	0.77	6.19	0.87
7. Services	272	6,618	16,167	194,026	38.7	1.05	0.42	2.51	0.05	1.95	0.70	5.60	0.85
8. Technology	134	37,770	114,662	1,084,704	131.8	1.18	0.46	2.79	0.34	2.04	0.73	5.03	0.81
9. Utilities	87	7,838	15,367	129,458	119.5	0.86	0.35	2.24	0.19	1.34	0.58	4.23	0.68
Total sample	*1373*	*19,091*	*119,636*	*2,701,406*	*38.7*	*1.11*	*0.48*	*3.23*	*0.05*	1.86	*0.78*	*11.50*	*0.63*

Table 2: Descriptive statistics of the recommendation revisions in the working sample

Panel A: Recommendation revisions by categories before revision			
Category before revision	Number of recommendation revisions		
	Upgrades	Downgrades	Total
1	0	61	61
2	69	975	1044
3	972	329	1301
4	329	8	337
5	3	0	3
Total	*1373*	*1373*	*2746*
Panel B: Recommendation revisions by number of categories changed in the revision			
Number of categories changed in the revision	Number of recommendation revisions		
	Upgrades	Downgrades	Total
1	1336	1337	2673
2	33	33	66
3	3	3	6
4	1	0	1

Total	*1373*	*1373*	*2746*
Panel C: Recommendation revisions by calendar years			
Year	Number of recommendation revisions		
	Upgrades	Downgrades	Total
2001	11	13	24
2002	17	23	40
2003	42	46	88
2004	73	79	152
2005	234	224	458
2006	996	988	1984
Total	*1373*	*1373*	*2746*

Table 3: Descriptive statistics of the event-date clustering

No. of events per day	No. of days	
	Upgrades	Downgrades
1	232	252
2	101	95
3	51	57
4	36	24
5	24	16
6	18	11
7	19	14
8	9	10
9	7	10
10	6	8
11	2	3
12	1	7
13	4	3
14	0	1
Total	510	511

Table 4: Average abnormal returns (ARs) around recommendation revisions

Days relative to event	Upgrades		Downgrades	
	Average AR, %	t-statistic	Average AR, %	t-statistic
-30 to -3	*** -1.88	-7.03	***1.89	7.92
-10 to -3	*** -0.69	-4.73	***0.54	4.15
-2	** -0.15	-2.43	*0.11	1.77
-1	***0.39	5.34	**-0.17	-2.17
0	***2.45	29.53	***-2.38	-26.97
1	0.04	0.66	***-0.15	-2.93
2	-0.01	-0.22	***-0.21	-4.51
3 to 10	**0.30	2.50	-0.11	-0.84

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 5: Effect of outcome availability on event-days ARs

Type of recommendation revision	Average AR on Day -1, %			Average AR on Day 0, %		
	$MR_{-1}>0$	$MR_{-1}<0$	Difference (t-statistic)	$MR_0>0$	$MR_0<0$	Difference (t-statistic)
Upgrades	0.68	0.02	***0.66 (4.54)	2.82	1.89	***0.93 (5.54)
Downgrades	0.22	-0.75	***0.98 (6.14)	-1.82	-3.04	***1.22 (7.00)

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 6: Effect of outcome availability on event-driven ARs, by market capitalization and beta groups: Upgrades, Day0

Panel A: ARs on days of positive and negative market returns				
Average AR on days of positive/negative MR_0, % (No. of events)				
Beta / Market capitalization	Low	Medium	High	Total
High	1.60/1.14 (176)	1.25/1.53 (149)	1.49/0.87 (130)	1.47/1.21 (455)
Medium	2.81/2.23 (169)	2.86/1.66 (150)	3.40/2.00 (149)	3.02/1.98 (468)
Low	3.83/1.70 (92)	3.74/2.59 (174)	4.04/3.12 (184)	3.88/2.56 (450)
Total	2.50/1.69 (437)	2.74/1.93 (473)	3.16/2.04 (463)	2.82/1.89 (1373)

Panel B: Availability-driven AR differences				
AR difference (t-statistic)				
Beta / Market capitalization	Low	Medium	High	Total
High	*0.46 (1.66)	-0.28 (-0.99)	*0.62 (1.67)	0.26 (1.45)
Medium	0.58 (1.42)	***1.20 (2.72)	***1.40 (2.68)	***1.04 (3.93)
Low	**2.13 (2.52)	**1.15 (2.03)	0.92 (1.52)	***1.32 (3.58)
Total	***0.81 (2.98)	***0.81 (2.95)	***1.12 (3.51)	***0.93 (5.54)

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 7: Effect of outcome availability on event-driven ARs, by market capitalization and beta groups: Downgrades, Day 0

Panel A: ARs on days of positive and negative market returns				
Average AR on days of positive/negative MR_0, % (No. of events)				
Beta / Market capitalization	Low	Medium	High	Total
High	-1.08/-1.97 (197)	-1.26/-1.56 (139)	-1.38/-2.14 (124)	-1.22/-1.89 (460)
Medium	-1.89/-1.69 (180)	-1.62/-2.89 (135)	-1.89/-3.03 (132)	-1.81/-2.49 (447)
Low	-2.32/-4.38 (102)	-2.73/-3.67 (168)	-2.49/-5.20 (196)	-2.54/-4.45 (466)
Total	-1.60/-2.54 (479)	-1.90/-2.81(442)	-1.99/-3.78 (452)	-1.82/-3.04 (1373)
Panel B: Availability-driven AR differences				
AR difference (t-statistic)				
Beta / Market capitalization	Low	Medium	High	Total
High	***0.89 (2.71)	0.30 (0.98)	0.76 (1.65)	***0.67 (3.23)
Medium	-0.20 (-0.70)	***1.27 (2.82)	**1.14 (2.46)	***0.68 (3.01)
Low	**2.06 (2.02)	0.94 (1.58)	***2.71 (4.61)	***1.91 (4.82)
Total	***0.94 (3.32)	***0.91 (3.15)	***1.79 (5.49)	***1.22 (7.00)

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 8: Effect of outcome availability on event-driven ARs, by historical volatility of stock returns

Type of recommendation revision	Volatility of stock returns (No. of events)	Average AR, %			F-statistic (equality of AR differences between low and high volatility stocks)
Panel A: Day -1					
		$MR_{-1}>0$	$MR_{-1}<0$	Difference (t-statistic)	
Upgrades	High (463)	1.25	0.08	***1.17 (3.45)	***8.52
	Medium (453)	0.47	-0.09	**0.56 (2.48)	
	Low (457)	0.26	0.07	0.19 (0.34)	
Downgrades	High (453)	0.45	-0.96	***1.41 (4.33)	*2.88
	Medium (461)	0.21	-0.80	***1.01 (3.40)	
	Low (459)	0.04	-0.47	***0.51 (2.76)	
Panel B: Day 0					
		$MR_0>0$	$MR_0<0$	Difference (t-statistic)	
Upgrades	High (463)	3.63	2.05	***1.58 (4.17)	25.11***
	Medium (453)	2.91	2.00	***0.91 (3.45)	
	Low (457)	1.78	1.65	0.13 (0.72)	
Downgrades	High (453)	-2.31	-4.00	***1.69 (3.69)	36.44***
	Medium (461)	-1.80	-3.24	***1.44 (4.41)	
	Low (459)	-1.41	-1.70	*0.29 (1.81)	

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 9: Multifactor regression analysis of event-driven ARs: Effect of outcome availability

Explanatory variables	Regression coefficients	Coefficient estimates, % (t-statistics)			
		Upgrades		Downgrades	
		Day -1	Day 0	Day -1	Day 0
MR_dum	γ_1	***0.66 (4.53)	***0.88 (5.46)	***0.95 (5.91)	***1.06 (6.29)
MCap	γ_2	-0.02 (-0.30)	***-0.70 (-8.26)	0.02 (0.19)	***0.62 (6.73)
beta	γ_3	-0.10 (-1.24)	-0.12 (-1.27)	*-0.18 (-1.85)	0.01 (0.07)
SR_volat	γ_4	***0.23 (2.59)	***0.36 (3.71)	0.17 (1.62)	***-0.49 (-4.39)
Magnitude	γ_5	0.69 (1.56)	-0.33 (-0.67)	0.76 (1.59)	-0.66 (-1.29)
AR_30_2	γ_6	-0.08 (-1.20)	*-0.15 (-1.90)	*** 0.24 (2.86)	0.10 (1.10)
from1[a]	φ_1			***-1.96 (-2.59)	***-2.15 (-2.66)
from2	φ_2	**-1.32 (-2.38)	***1.88 (3.07)	***-1.49 (-2.91)	***-2.24 (-4.16)
from3	φ_3	-0.66 (-1.42)	***2.38 (4.63)	***-1.76 (-3.41)	***-2.53 (-4.64)
from4	φ_4	-0.74 (-1.46)	***1.86 (3.30)	-0.84 (-0.74)	-0.58 (-0.48)
from5[a]	φ_5	-1.42 (-0.66)	1.92 (0.82)		

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01
[a]Dummy variable *from5i* (*from1i*) is included in the regression analysis only for upgrades (downgrades).

Table 10: Effect of outcome availability on event-days cumulative ARs

Type of recommendation revision	Cumulative Average AR over Days -1 and 0, %		
	$MR_{-1\_0}>0$	$MR_{-1\_0}<0$	Difference (t-statistic)
Upgrades	3.16	2.40	***0.76 (3.50)
Downgrades	-2.08	-3.14	***1.06 (4.52)

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 11: Effect of outcome availability on abnormal trading volumes on Day 0

Type of recommendation revision	Average abnormal volume on Day 0		
	$MR_0>0$	$MR_0<0$	Difference (t-statistic)
Upgrades	1.91	1.55	***0.36 (3.00)
Downgrades	1.50	2.13	***-0.63 (-4.85)

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 12: Multifactor regression analysis of day-0 abnormal trading volume: Effect of outcome availability

Explanatory variables	Regression coefficients	Coefficient estimates, (t-statistics)	
		Upgrades	Downgrades
MR_dum0	γ_1	***0.38 (3.23)	***-0.59 (-4.66)
MCap	γ_2	***-0.37 (-5.97)	***-0.45 (-6.48)
beta	γ_3	0.10 (1.47)	***0.23 (2.95)
SR_volat	γ_4	***-0.20 (-2.91)	***-0.46 (-5.41)
Magnitude	γ_5	**0.77 (2.15)	0.25 (0.64)
AR_30_2	γ_6	-0.01 (-0.21)	***-0.20 (-2.89)
from1[a]	φ_1		**1.41 (2.32)
from2	φ_2	0.37 (0.84)	***1.90 (4.67)
from3	φ_3	**0.89 (2.36)	***2.03 (4.90)
from4	φ_4	0.44 (1.07)	0.17 (0.19)
from5[a]	φ_5	-1.97 (-1.15)	

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

[a]Dummy variable *from5* (*from1*) is included in the regression analysis only for upgrades (downgrades).

Table 13: Combined effect of outcome and risk availability: Regression analysis

Explanatory variables	Regression coefficients	Coefficient estimates, % (t-statistics)	
		Upgrades	Downgrades
Intercept	γ_0	***2.04 (13.90)	***-2.92 (-19.76)
MR_dum0	γ_1	***0.94 (5.61)	***1.20 (6.91)
subret	γ_2	**-0.36 (-2.18)	*-0.31 (-1.72)

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 14: Combined effect of outcome and risk availability: Sample partition by MR direction and MR magnitude

Panel A: Recommendation upgrades			
Sample partition	Average AR on Day 0, % (No. of events)		Difference (t-statistic)
MR magnitude	Substantial MRs (589)	Non-Substantial MRs (784)	
MR direction			
MR_0>0 (826)	2.47 (364)	3.09 (462)	***-0.62 (-2.65)
MR_0<0 (547)	1.91 (225)	1.87 (322)	0.04 (0.17)
Difference (t-statistic)	**0.56 (2.31)	***1.22 (5.32)	

Panel B: Recommendation downgrades			
Sample partition	Average AR on Day 0, % (No. of events)		Difference (t-statistic)
MR magnitude	Substantial MRs (522)	Non-Substantial MRs (851)	
MR direction			
$MR_0>0$ (746)	-1.93 (266)	-1.76 (480)	-0.17 (-1.01)
$MR_0<0$ (627)	-3.31 (256)	-2.85 (371)	-0.46 (-1.39)
Difference (t-statistic)	***1.38 (4.58)	***1.09 (5.16)	

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 15: Combined effect of outcome and risk availability: Multifactor regression analysis

Explanatory variables	Regression coefficients	Coefficient estimates, % (t-statistics)	
		Upgrades	Downgrades
MR_dum0	γ_1	***0.89 (5.56)	***1.05 (6.23)
Subret	γ_2	***-0.44 (-2.80)	-0.21 (-1.22)
MCap	γ_3	***-0.71 (-8.37)	***0.62 (6.72)
beta	γ_4	-0.11 (-1.21)	0.01 (0.01)
SR_volat	γ_5	***0.35 (3.71)	***-0.48 (-4.31)
Magnitude	γ_6	-0.39 (-0.79)	-0.67 (-1.31)
AR_30_2	γ_7	*-0.15 (-1.92)	0.09 (0.96)
from1[a]	φ_1		**-2.06 (-2.55)
from2	φ_2	***2.15 (3.49)	***-2.14 (-3.94)
from3	φ_3	***2.63 (5.05)	***-2.43 (-4.40)
from4	φ_4	***2.09 (3.68)	-0.54 (-0.45)
from5[a]	φ_5	2.25 (0.96)	

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01
[a]Dummy variable *from5* (*from1*) is included in the regression analysis only for upgrades (downgrades).

Table 16: Effect of risk availability on Day-0 abnormal trading volumes

Panel A: Day-0 abnormal volumes on the days of substantially positive and substantially negative MRs			
Type of recommendation revision	Average abnormal volume on Day 0		
	Substantially positive MRs	Substantially negative MRs	Difference (t-statistic)
Upgrades	1.67	1.63	0.04 (0.25)
Downgrades	1.67	2.27	***-0.60 (-2.81)
Panel B: Day-0 abnormal volumes on the days of substantial and non-substantial MRs			
Type of recommendation revision	Average abnormal volume on Day 0		
	Substantial MRs	Non-Substantial MRs	Difference (t-statistic)
Upgrades	1.66	1.86	*-0.20 (-1.72)
Downgrades	1.97	1.68	**0.29 (2.16)

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01

Table 17: Multifactor regression analysis of day-0 abnormal trading volume: Effect of risk availability

Explanatory variables	Regression coefficients	Coefficient estimates, (t-statistics)	
		Upgrades	Downgrades
Subret	γ1	*-0.22 (-1.90)	*0.25 (1.95)
MCap	γ2	***-0.37 (-6.01)	***-0.47 (-6.71)
beta	γ3	0.10 (1.52)	***0.23 (2.92)
SR_volat	γ4	***-0.19 (-2.76)	***-0.45 (-5.29)
Magnitude	γ5	*0.70 (1.94)	0.24 (0.60)
AR_30_2	γ6	-0.01 (-0.22)	***-0.19 (-2.77)
from1[a]	φ1		0.95 (1.56)
from2	φ2	*0.76 (1.69)	***1.49 (3.65)
from3	φ3	***1.28 (3.42)	***1.63 (3.90)
from4	φ4	**0.85 (2.08)	-0.17 (-0.18)
from5[a]	φ5	-1.41 (-0.82)	

Asterisks denote 2-tailed p-values: *p<0.10; **p<0.05; ***p<0.01
[a]Dummy variable *from5* (*from1*) is included in the regression analysis only for upgrades (downgrades).

Figure 1: Cumulative average daily ARs around recommendation upgrades

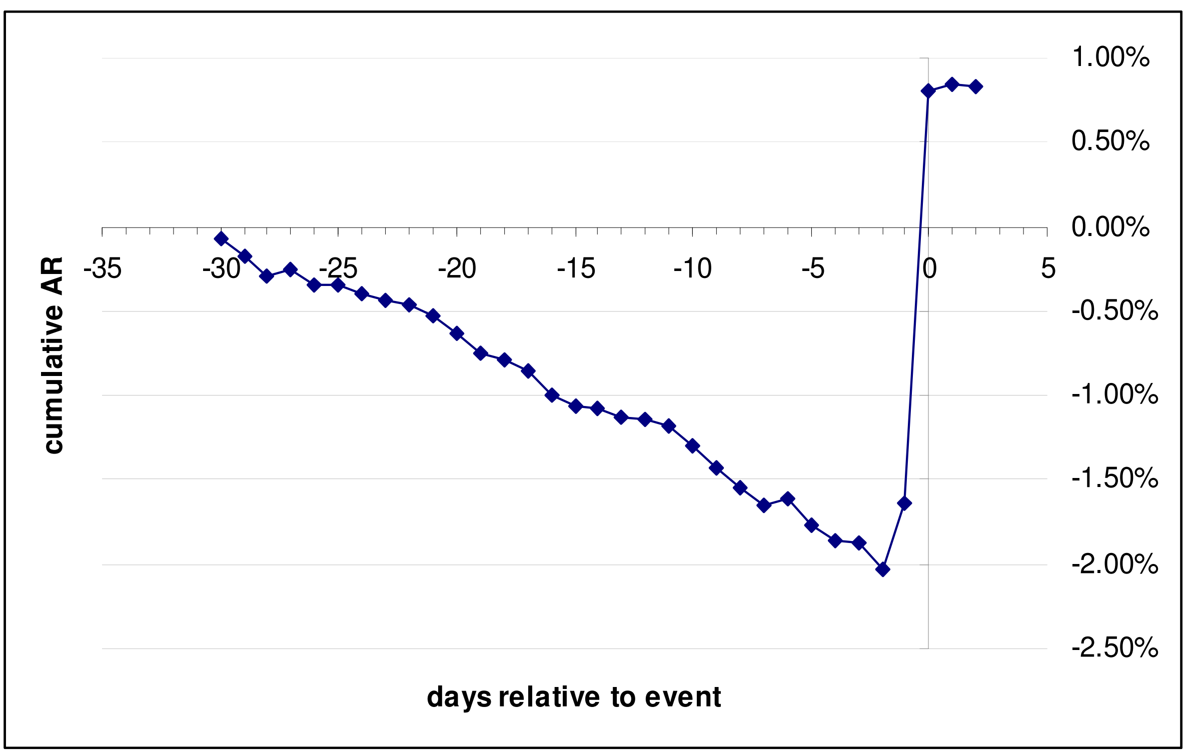

Figure 2: Cumulative average daily ARs around recommendation downgrades