Media and Investors' Attention. Estimating analysts' ratings and sentiment of a financial column to predict abnormal returns

L'attenzione dei media e degli investitori. Stima del voto degli analisti e del sentiment di una rubrica finanziaria per predire i ritorni anomali

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Abstract In line with the attention grabbing theory, the publication of articles dealing with the profile of single listed companies along with financial analysts' recommendations is followed by significant increases when the recommendation is positive. In this paper, we tried to understand what happens when analysts' recommendations are missing. We estimated analysts' recommendations with a classification based on the terms in the articles and through a sentiment analysis of the same texts. Results showed that investors transform the articles' content into implicit recommendations that guide their buying decisions when the sentiment is highly positive.

Abstract *In linea con la teoria dell'attention grabbing, la pubblicazione di articoli che trattano il profilo di singole società quotate e le raccomandazioni degli analisti finanziari è seguita da incrementi significativi quando la raccomandazione è positiva. In questo paper abbiamo cercato di capire cosa succede in assenza delle raccomandazioni degli analisti, che abbiamo cercato di stimare sulla base dei termini presenti negli articoli o di approssimare tramite sentiment analysis degli articoli stessi. I risultati indicano che gli investitori trasformano il contenuto degli articoli in raccomandazioni implicite che orientano le loro decisioni di acquisto se il sentiment risulta molto positivo.*

Key words: text mining, sentiment, classification, event study, abnormal returns

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1 Introduction

This paper deals with market reaction to second-hand news published on the Sunday editions of an Italian financial newspaper. Stale information published in print media can lead retail investors to buy stocks that grab their attention (Barber and Odean, 2008) such that past analysts' recommendations induce abnormal movements in stock prices and returns (Cervellati et al., 2014). Previous research (Ferretti and Sciandra, 2020), analyzed the column 'Letter to investor', which appeared in the top Italian financial newspaper (Il Sole 24 Ore) from 2005 to 2010. From 2011 until now, the column has changed the author of these articles, keeping practically unchanged contents, structure, and layout. The only exception is that this new version no longer publishes the analysts' rating (positive or not). Specifically, Cervellati et al. (2014) and Ferretti and Sciandra (2020) showed that the publication of articles concerning the profile of single listed companies and the recommendations of financial analysts are followed by an asymmetric reaction of stock prices. In particular, they find a statistically significant increase when the recommendation is positive (overweight or buy) and a substantial stationarity when the recommendation is not positive (hold or underweight or sell). This is precisely what is suggested by Barber and Odean's theory of attention grabbing (2008). The Attention-Grabbing Hypothesis (AGH) assumes that naïve investors' behavior affects the market. AGH predicts positive and significant abnormal returns for positively recommended stocks and no reaction for negative ratings. In other words, the market reaction is motivated by an attention-grabbing phenomenon, because only the publication of positive recommendations induces a significant (positive) price movement. Attention grabbing only addresses buying decisions of investors and only when their buying intention is supported by a positive recommendation. So, the research question that arises is what would be the investors' behavior when an explicit recommendation is missing. We identified three possible scenarios: (i) the attention grabbing resulting from the publication of the article affects buying intentions indistinctly, i.e., all articles are perceived as positive recommendations; (ii) the absence of explicit buying or selling indications causes attention to remain in a latent state (no action); (iii) investors transform the content of columns into implicit recommendations which, if positive, guide their buying decisions.

Our analysis strategy to identify the most likely scenario involves: i) evaluating the existence of the attention grabbing mechanism by means of an event study on the whole new sample of observations (2011-2020); ii) reproducing the analysts' ratings in the sample 2005-2010 by means of a statistical model based only on the words appearing in the articles, then estimating the analysts' rating in the new sample; iii) evaluating the existence of significant differences in abnormal returns - on the day after news publication (day 0) - according to the estimated analysts' rating. If no significant differences exist, we plan to assess whether the presence of implicit recommendations in the text of the articles, approximated by a tone (sentiment) analysis, can affect buying decisions.

2 Data collection and methods

We collected all the ‘Letter to investor’ columns published from January 2005 to December 2020 that were devoted to domestic companies listed on the Italian Stock Exchange. The final dataset consists of 870 records. For the first part of the sample (2005-2010 – panel A: 379 records[1]) analysts' ratings were available together with the columns’ texts, while from 2011 (2011-2020 – panel B: 491 cases) only columns’ texts were available.

As first step to answer our research question we conducted a standard event study (Brown and Warner, 1985) on returns in the Panel B. The event day (t=0) is the Monday following each column. The event window went from day -3 to day +3. When an explicit analysts’ recommendation is missing, if we found significant abnormal returns on the event day, this could suggest that the publication of the column affected buying intentions indistinctly (scenario (i)), otherwise the absence of explicit buying advice caused no action (scenario (ii)).

To predict the analysts’ recommendations in the panel B, we first estimated the analysts’ ratings (‘buy’ or ‘don’t buy’) in Panel A exploiting the actual variable (analysts’ rating - binary) and the columns’ texts through some text mining and data mining techniques. Next, we classified the columns of Panel B with the best model found in Panel A in terms of accuracy. Based on this new classification on Panel B, we conducted another event study by separating estimated positive recommended columns and non-positive recommended columns. To confirm the event study results, we would also run a regression model, including potential confounding variables (see Table 4) along with the estimated rating. If we did not find significant differences in abnormal returns on the event day, then again, the attention grabbing would affect buying intentions indistinctly. Otherwise, we speculated about investors transforming the columns’ content into implicit recommendations which can lead their buying decisions. In this case we planned to perform a sentiment analysis on Panel B texts and then split this sample (positive vs non-positive, or highly-positive vs positive) applying an event study and a regression analysis. If sentiment turned out to be a significant variable for abnormal returns, then we would be in scenario (iii). To exploit textual data by classifying analysts’ ratings and extracting columns’ sentiment, we first performed a text pre-processing, in particular by removing numbers and Italian ‘stop words’ (articles, prepositions, pronouns, etc.), and recoding some potentially interesting multi-word expressions into n-grams. Then we created a document-term matrix (about 16000 terms for Panel A) and select a limited number of potential features (81) based on their document frequency (at least 5% of all documents) and words’ odds ratio from positive or non-positive analysts’ ratings. Instead of a word count, we decided to use a binary coding, indicating the presence/absence of a given term in each column. This choice allowed us to limit the incidence of different text lengths and styles, usually without significantly decreasing the reliability of the statistical analysis (Ceron et al., 2017). To extract a sentiment measure for each column of Panel B, we exploited an

[1] Panel A included also ‘The Stock of the Week’ column, which appeared on the Saturday editions of ‘Il Sole 24 ore’ from 2005 to 2010 with very similar contents to the ‘Letter to investor’.

ontological dictionary, the NRC lexicon (Mohammad and Turney, 2012). The sentiment score showed 49 different levels, all of them with a positive sign, so we decided to use the median value to split our sample into two group, positive' and 'highly-positive', for the event study and to use the score as an independent variable in the regression model for abnormal returns (ARs).

3 Results

A summary of the event study for Panel B is reported in Table 1: from day from -3 to day +3 only the ARs of day 0 were statistically significant and the same went for the sign test (T2). We computed the ARs with two methods: the Market Adjusted Model and the standard one-factor Market Model. Moreover, we also computed ARs in the sample excluding cases with concurrent news. All models lead to similar results; therefore, we only show the results for the Market Adjusted Model: $AR_{jt} = R_{jt} - R_{mt}$; where R_{jt} is the stock return of company j on day t, R_{mt} is the stock market return (MILAN COMIT GLOBAL + R - PRICE INDEX) on day t, and AR_{jt} is the abnormal return of company j on day t (AR_{jt} are averaged across companies to get the mean Abnormal Return on day t, AR_t).

Table 1: Panel B (491 records): Event study for daily Abnormal Returns (ARs) - Market Adjusted Model

Day		*ARt %*	*T*	*T2*
Wednesday	-3	-0.094	-1.04	-0.36
Thursday	-2	-0.085	-0.95	-1.35
Friday	-1	0.085	0.94	-0.81
Monday	0	0.275	3.05*	2.26*
Tuesday	1	0.095	1.05	1.00
Wednesday	2	-0.069	-0.76	-1.08
Thursday	3	-0.010	-0.12	0.27

* denote significance at the 5% level. T= t-test. T2= nonparametric sign test (Ocana et al., 2002).

This first analysis reveals a significant market reaction to Panel B columns even without a clear analysts' recommendation, suggesting the possibility that (when a clear buy recommendation is missing) the inclusion of a stock in the column might affect buying decisions indistinctly with respect to what might be revealed by the text. Next, we tried to estimate the analyst rating in Panel A (where the rating was available) and predict it in Panel B, solely based on the words in the column texts. To achieve this goal, we classified analysts' rating with some data mining fitting techniques (Hastie et al., 2009): Probit, Logit, Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Neural Networks, and Naïve Bayes. Considering the sample size of 379 for Panel A, we chose the optimistic corrected bootstrap (Efron and Tibshirani, 1993) as the resampling method for model validation, in order to obtain measures with less variance. QDA turned out to be the best classifier in terms of accuracy and Cohen's kappa (Table 2), and this model was used to predict the analysts' rating in Panel B.

Table 2: 200 bootstrap accuracy of analysts' rating classifiers (Panel A) – features: 81 words or n-grams

Classifier	*Accuracy*	*Kappa*
Probit	0.728	0.432
Logit	0.750	0.491
LDA	0.752	0.494
QDA	0.838	0.660
Neural Networks	0.802	0.597
Naïve Bayes	0.687	0.358

Despite a decent level of accuracy in Panel A, in the event study for Panel B, splitting the sample between positive and non-positive estimated stocks, the ARs are positive and significant in both groups on day 0, but of greater magnitude for non-positive ratings. The linear regression estimating ARs also shows the non-significance of the rating, both as a stand-alone variable or in interaction with the other predictors. This poor performance could also be related to the discontinuity in the column's author. Thus, to confirm scenario (i) or to imply that investors transform the content of the column into implicit recommendations, we used the results of the sentiment analysis applied to Panel B. As anticipated, we divided Panel B into two groups of stocks, positive and highly-positive, and applied an additional event study to the two groups. The results (Table 3) show an asymmetric reaction, as highly-positive stocks reported significantly higher ARs than positive stocks. Linear regression (Table 4) also shows that the sentiment variable turned out to be a significant predictor alone or in interaction with other variables.

Table 3: Panel B: Event study for daily Abnormal Returns (ARs) - Market Adjusted Model

	Positive sentiment				*Highly-positive sentiment*			
Day	*Obs.*	*ARt %*	*T*	*T2*	*Obs.*	*ARt %*	*T*	*T2*
-3	254	-0.262	-2.19*	-0.87	237	0.087	0.67	0.39
-2	254	-0.196	-1.64	-1.13	237	0.033	0.25	-0.78
-1	254	0.082	0.68	-1.88	237	0.088	0.67	0.78
0	254	0.191	1.59	0.38	237	0.366	2.80*	2.86*
1	254	0.084	0.70	0.38	237	0.107	0.82	1.04
2	254	0.012	0.10	-0.12	237	-0.156	-1.20	-1.43
3	254	-0.009	-0.07	-0.25	237	-0.012	-0.09	0.65

* denote significance at the 5% level. T= t-test. T2= nonparametric sign test (Ocana et al., 2002).

Table 4: Linear regression for Panel B Abnormal Returns - Market Adjusted Model

Variable	*Estimate*	*Std. Error*	*T value*	*Pr(>|t|)*
(intercept)	-3.88e-02	1.838e-02	-2.111	0.035*
PBV	-1.404e-03	9.656e-04	-1.454	0.147
Market Capit. (ln)	8.685e-03	2.691e-03	3.228	0.001**
Past Performance	3.111e-02	1.335e-02	2.330	0.020*
Beta	-2.513e-02	9.805e-03	-2.563	0.011*
Concurrent News	-2.177e-02	7.912e-03	-2.751	0.006**
Sentiment	1.777e-03	6.372e-04	2.789	0.005**
Sentiment*Market Capit (ln)	-3.283e-04	9.493e-05	-3.459	<0.001***
Sentiment*Beta	6.906e-04	3.126e-04	2.209	0.028*
Sentiment*Concurrent News	7.237e-04	2.685e-04	2.695	0.007**
Sentiment*PBV	3.975e-05	3.046e-05	1.305	0.192
Sentiment*Past Performance	-6.565e-04	4.639e-04	-1.415	0.158

***, ** and * denote significance at the 0.1%, 1% and 5% levels. The table reports a linear regression model for the abnormal returns (ARs). Explanatory variables include Price-to-book value (PBV), company's market capitalization, Market-adjusted company's past performance (stock return from day -215 to day -16 before the event day, net of the market return in the same period), risk (Market-model Beta), a dummy variable indicating the presence of concurrent news (the dummy variable equals 1 if the company reported in the column published press releases in day 0 or in day +1), columns' sentiment, and the interactions among the sentiment and all other explanatory variables. We show the estimated coefficients, the SEs, the t values, and the significance levels associated with each explanatory variable or interaction. The adjusted R-squared is 0.071 (F-statistics: 4.398, p-value: 2.62e-06).

4 Conclusion

The final results of the event study and the regression based on the sentiment of the columns without analysts' recommendations suggest that investors transform the content of the articles into implicit recommendations that, when (highly) positive, can direct their buying decisions. In future studies, we plan to investigate the use of lexicons specifically developed for financial texts since, as far as we know, there are no Italian ontological dictionaries for finance, as it happens in English, where the work of Loughran and McDonald (2011) has been widely used.

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