Does investor attention influence stock market activity? The case of spin-off deals

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Does investor attention influence stock market activity? The case of spin-off deals

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Abstract

This paper investigates empirically the nature of the interactions between mass media, investor attention and the stock market using data from a sample of 16 spin-off deals traded on NYSE and published between 2004 and 2010 in "Wall Street Journal", the US's second-largest newspaper by circulation.

The results show that: i) the impact of media sentiment on the stock market reactions is enhanced / moderated by the level of attention of investors; ii) individual investors' attention is grabbed by stocks experiencing high trading volumes on the previous day; iii) high attention could result in downward pressure on stock market returns.

Keywords: Media Sentiment, Investor Attention, Internet Search, Spin-off
JEL Classifications: G10, G34

1. Introduction

One of the most important research streams in finance is to understand the determinants of stock market dynamics. According to the theory of efficient financial markets (Fama, 1970), stock prices should reflect all available information. However, the evidence of an autocorrelation of stock returns at short horizons (Jegadeesh and Titman, 1993; Moskowitz and Grinblatt 1999; Hong, Touros, and Valkanov, 2007) suggests that that stock prices do not fully adjust to new information.

In recent times, a number of studies have been conducted to explain stock market underreaction / overreaction to new information. In particular, these models rely on underreaction due to investor sentiment and conservatism when adjusting beliefs (Barberis, Shleifer, and Vishny 1998), variations in investor confidence arising from biased self-attribution (Daniel, Hirshleifer, and Subrahmanyam, 1998) and slow information diffusion (Hong and Stein, 1999).

A way to test these models is to consider market sentiment as a measure of investor expectation about future stock returns and attention allocation as a proxy for either investors' cognitive biases or information diffusion.

In this regard, market sentiment is made up by different sources of information: press releases, analysts' comments and mass media are just few examples. An intriguing literature provides interesting evidence of the impact of these different sources on various stock market variables, such as returns, trading volumes, and price volatility (Dell'Acqua, Perrini and Caselli, 2010; Doukas, Kim and Pantzalis, 2005; Antweiler and Frank, 2004; Coval and Shumway, 2001).

Dell'Acqua, Perrini and Caselli (2010) find evidence that voluntary disclosure following the introduction of the Regulation Fair Disclosure, included in the Selective Disclosure and Insider Trading Act issued by the SEC, reduces price volatility of high tech firms listed in the US market. Doukas, Kim and Pantzalis (2005) find that positive excess analyst coverage, raising investors optimism, is associated with overvaluation and low future returns. Antweiler and Frank (2004) find evidence of a relationship between message activity and both trading volume and return volatility. Similarly, Coval and Shumway (2001) establish that the ambient noise level created by traders in a futures pit is linked to volume and volatility, but not to returns. In addition, Tetlock, Saar-Tsechansky and Mackassy (2008) find that some news exerts an effect in a relatively short period while other news in the medium and long term (for example, news regarding core aspects of firm management).

As shown by various cognitive studies (Baumeister, Bratslavsky, Finkenauer and Vohs, 2001; Rozin and Royzman 2001; Fiske and Taylor, 1991; Brief and Motowidlo, 1986), positive and negative news have different impacts on people' perceptions, and negative news also exerts a stronger impact than positive news. Moreover the emotion aroused by news is likely to influence investors' behaviour (Carretta, Farina, Fiordelisi, Martelli and Schwizer 2011). Shoemaker and Reese (1996) argue that newspapers generally tend to put certain emphasis in the news in order to make it more engaging to the public. As a consequence, financial journalists may tend to "dramatize" corporate events in order to make their articles more interesting for the public of investors.

Theoretically, one could expect a variation in stock market activity as a consequence of a shock in the levels of attention (Daniel, Hirshleifer and Subrahmanyam, 1998; Hong and Stein, 1999). Various empirical studies document this impact (Chemmanur and Yan, 2009; Da, Engelberg and Gao, 2009; DellaVigna and Pollet, 2009; Barber and Odean 2008; Cohen and Frazzini, 2008; Peng, Xiong and Bollerslev, 2007; Fehle, Tsyplakov and Zdorovtsov, 2005; Huberman and Regev, 2001).

Chemmanur and Yan (2009) find that an increased level of investor attention is associated with a larger contemporary stock return and a smaller future stock return. Da, Engelberg and Gao (2009) find investor attention to be correlated with the large first-day return and the long-run underperformance of IPO stocks.

DellaVigna and Pollet (2009) compare the response of stock returns to earnings announcements on Friday, when investors are more likely to be inattentive, and on other weekdays. They find that the volume reaction and the two-day stock price reaction to news that is released to the media on Fridays are much weaker than when news is released on other days of the week. Barber and Odean (2008) test and confirm the hypothesis that individual investors are net buyers of attention-grabbing stocks, e.g., stocks in the news, stocks experiencing high abnormal trading volume, and stocks with extreme one day returns. Therefore individual investors are more prone to search for information when they are buying since they have to choose from a large set of available alternatives.

Cohen and Frazzini (2008) put in evidence that in the presence of investors subject to attention constraints, stock prices do not promptly incorporate news about economically related firms. Peng, Xiong and Bollerslev (2007) find supports for the hypothesis that investors shift their (limited) attention to processing market level information following an increase in market wide uncertainty and then subsequently divert their attention back to asset specific information. Fehle, Tsyplakov and Zdorovtsov (2005) examine whether companies can create attention effects through advertising. Investigating stock price reactions and trading activity for firms employing TV commercials in 19 Super Bowl broadcasts over the period 1969-2001, they find significant positive abnormal returns for firms which are readily identifiable from the contents.

Huberman and Regev (2001) compare the effect of information published by the popular New York Times versus the effect of the same information published by the journal Nature and by various popular newspapers (including the Times) more than five months earlier. Results show as newspaper content can affect stock prices even if the content does not provide genuine information thus confirming the important role exercised by investor attention.

This paper aims to test whether and how market sentiment (arising from mass media) and investor attention play a role in influencing the performance of spin-off deals, back in fashion due to the recent financial crisis. We use data from a sample of 16 spin-off deals published between 2004 and 2010 in "Wall Street Journal", the US's second-largest newspaper by circulation. In detail, we expect that media sentiment and investor attention will influence investor reaction around the data of various spin-off deals and on the subsequent days.

From a theoretical point of view, we broaden the literature on stock market reaction to spin-off deals. Firms on the stock markets have spun off bits of themselves as separate listed companies worth a total of $54 billion in all of 2010 worldwide (source: Economist 2011). One of the main reasons for the starburst is that companies seeking buyers for parts of their business are not getting good offers from other firms, or from private equity. Another driving force is the "conglomerate discount" when stock markets value a diversified group at less than the sum of its parts.

Existing studies on this topic consider investors' reaction and performance in relation to (Chemmanur, Jordan, Liu, Wu, 2010; Veld and Veld-Merkoulova, 2009; Chemmanur and Yan, 2004; Veld and Veld-Merkoulova, 2004; Desai and Jain, 1999; Daley, Mehrotra and Sivakumar, 1997; Cusatis, Miles and Woolridge, 1993; Rosenfeld, 1984; Schipper and Smith, 1983; Miles and Rosenfeld, 1983; Hite and Owers, 1983): i) spin-off size, ii) improvement of industrial focus, iii) information asymmetry, iv) regulatory and tax advantages, v) anti-takeover provisions.

From a methodologically point of view, we consider mass media content as a measure of investor expectation about future stock returns and attention allocation as a proxy for either investor cognitive biases or information diffusion.
Moreover, we define a direct measure of investor attention using data from Google Insights for Search. Since, internet users commonly use a search engine to collect information, aggregate search frequency in this search engine could be considered a direct and unambiguous measure of attention (Da, Engelberg and Gao, 2009).
Finally, we examine the statistical relation between investors' attention and stock market variables using a dynamic model built as a sparse structural vector autoregression (SVAR) and adopting an approach based on graphical modelling (Reale and Tunnicliffe Wilson, 2001).
The rest of this paper is organized as follows. In the next section we present data and variables. Section 3 lays out methods and estimation results. Finally, Section 4 concludes.

2. Data and variables

Our sample includes 16 spin-off deals (Table 1) traded on the New York Stock Exchange (NYSE) and published between 2004 and 2010 in "Wall Street Journal", the US's second-largest newspaper by circulation (according to Editor & Publisher, in 2010 it reported circulation of just over two million weekday copies).

Table 1. Sample of spin-off deals considered for the analysis

Spin-off	Parent Company
Acco Brand Corp. (Acco World Corp.)	Fortune Brands Inc
Ameriprise Financial Inc.	American Express Co
AOL	Time Warner
Broadridge Financial Solutions Inc	Automatic Data Processing Inc
CareFusion Corp	Cardinal Health Inc.
Cenovus Energy	EnCana Corp
Covidien PLC	Tyco International Ltd
Discover Financial Services	Morgan Stanley
Live Nation Entertainment Inc.	Clear Channel Communications Inc.
Mead Johnson Nutrition Co.	Bristol-Myers Squibb Co.
Motorola Mobility Holding Inc	Motorola Inc (Motorola Solution Inc)
Philip Morris International Inc.	Altria Group Inc
Primerica Inc.	Citigroup Inc
Spectra Energy Corp	Duke Energy Corp.
Teradata Corp	NCR Corp
Time Warner Cable Inc.	Time Warner Inc.

2.1 Media sentiment

We define media sentiment as the degree of positive or negative comments in the Wall Street Journal regarding each spin-off firm before the deal. This financial newspaper is considered as a natural choice for a data source that reflects and influences investor sentiment since it has a large diffusion and a strong reputation among the financial community (Tetlock, 2007).

First, all the news regarding spin-off deals of Wall Street Journal are extracted from the database Factiva, which provides access to more than 10,000 sources, including newspapers, magazines, news agencies and information sites.
Second we apply computer aided text analysis (Stone, Dunphy, Smith and Ogilvie, 1966) using the linguistic dictionary Harvard IV Psycho Social[1] and the software Wordsmith 4 (Scott, 2004).
Operationally, Wordsmith 4 counts the number of words in each news item that falls within the *positive* and *negative* categories of the Harvard IV Psycho Social Dictionary. In fact, each category contains a list of words and word senses. However, since some words in this list (such as mine, cancer or capital) are more likely to identify a specific industry segment than reveal negative financial events we used the revised list of Loughran and McDonald (2011) including words that typically have implications only in a financial sense. The negative category is larger, with 2,337 entries, while the positive category has 353 words and this difference in size could skew of the distributions for news content. Our choice is made for the following reasons: first, using a standard text analysis dictionary allows for the stability and the reproducibility of results; second, the problem of skewness is limited by considering the number of times different words of each category (positive/negative) are repeated in the text of the news.
Finally, the positive or negative sense of the news is determined by: P - N where P and N are, respectively, the number of positive and negative words in news.

2.2 Investor attention

To define a direct measure of investor attention, we use daily data from Google Insights for Search (http://www.google.com/insights/search/) for the considered sample of spin-offs. In fact, according to Da, Engelberg and Gao (2009), if someone searches for something in a search engine, he is certainly paying attention to it. Moreover the percent of global internet users visiting Google is 50,03% of internet users visiting at the March 30, 2011 (source: www.alexa.com).
Choi and Varian (2009) provide evidence that search data on Google may predict home sales, automotive sales and tourism. Another study of Ginsberg, Mohebbi, Patel, Brammer, Smolinski and Brilliant (2008) finds that search data for forty-five terms related to influenza predicted flu outbreaks one to two weeks before official reports. In detail, this tool analyzes a portion of worldwide Google web searches from all Google domains to compute how many searches have been done for the terms one have entered, relative to the total number of searches done on Google over time.
We applied the category filter Finance and Insurance in order to download the time series showing the monthly change of the searches over time expressed as a percentage of growth, with respect to the first date on the graph (or the first date that has data).
Finally investor attention is defined as a percentage of growth of aggregate search frequency in Google, with respect to the average value in the previous five days and for a period of three months from the deal.

2.3 Stock market

Data regarding stock market activity come from Datastream Database. In detail, the daily returns for each spin-off are calculated from the adjusted close prices. The variation in volumes is computed as the logarithmic difference with the previous day. Volatility is

[1] The original spreadsheet format can be downloaded at:
www.wjh.harvard.edu/~inquirer/spreadsheet_guide.htm

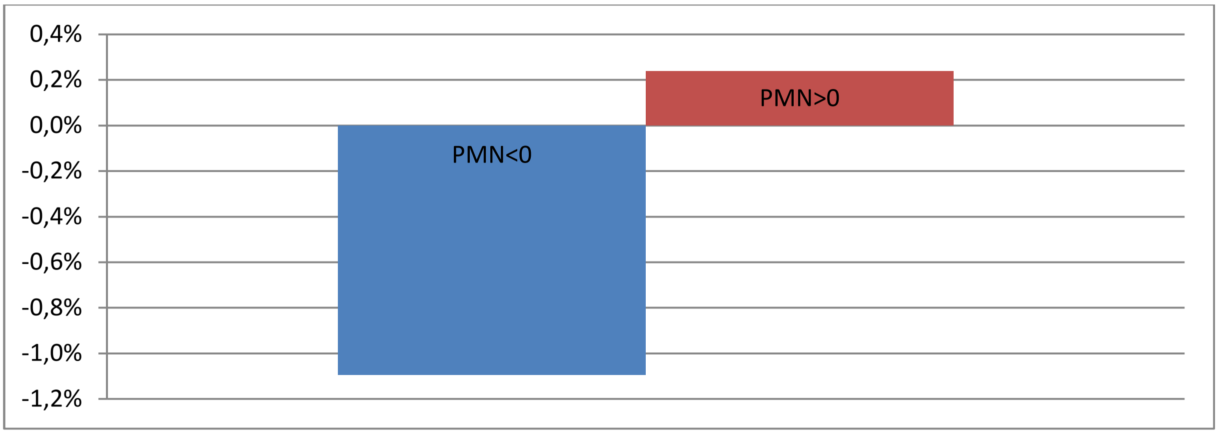
calculated as the standard deviation of spin-off returns. The daily market returns are based on Dow Jones Industrial Average (DJIA) Index.

3. Analysis

3.1. Descriptive analysis

Some interesting evidences come from descriptive analysis. First, we analyze the relation between media sentiment and spin-off returns. Figure 1 summarizes the main findings.

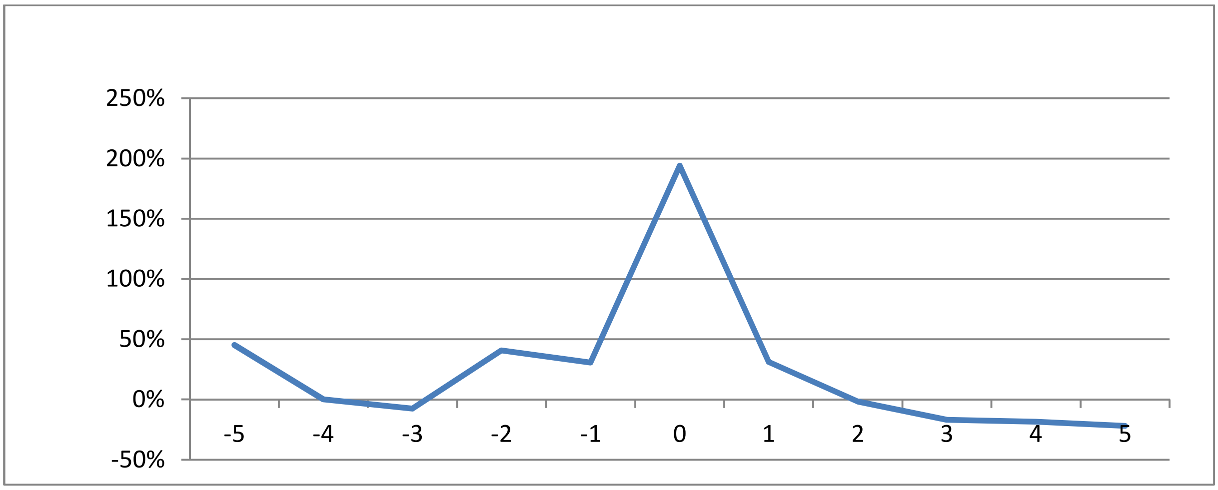
Figure 1. Media sentiment and percentage variation of spin-off returns after one day



We observe that the set of spin-offs anticipated with a positive sentiment have a positive variation of returns after the first-day of 0,24% on average, while the set of spin-offs anticipated with a negative sentiment have a negative variation of returns after one day from the deal equal to 1,09%. This is coherent with the hypothesis that media sentiment, measured as semantic content of the news, affects the investor behaviour around the spin-off date.

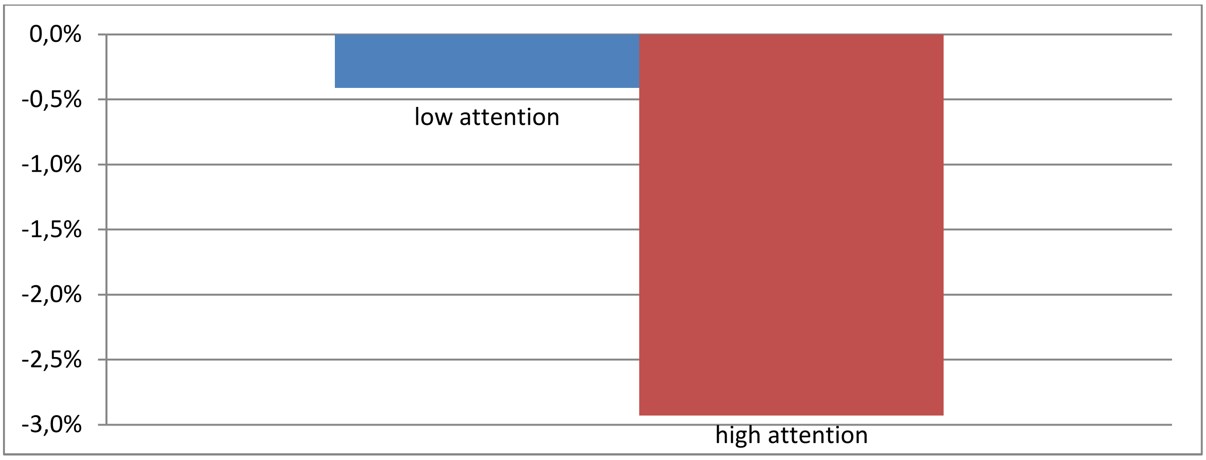
Second, we assess the change in investors' attention around a spin-off deal. Figure 2 confirms that there are significant changes in attention level around the date of spin-off deal (day 0).

Figure 2. Change in attention indicator series around the date (-5gg, +5gg) of spin-off deals



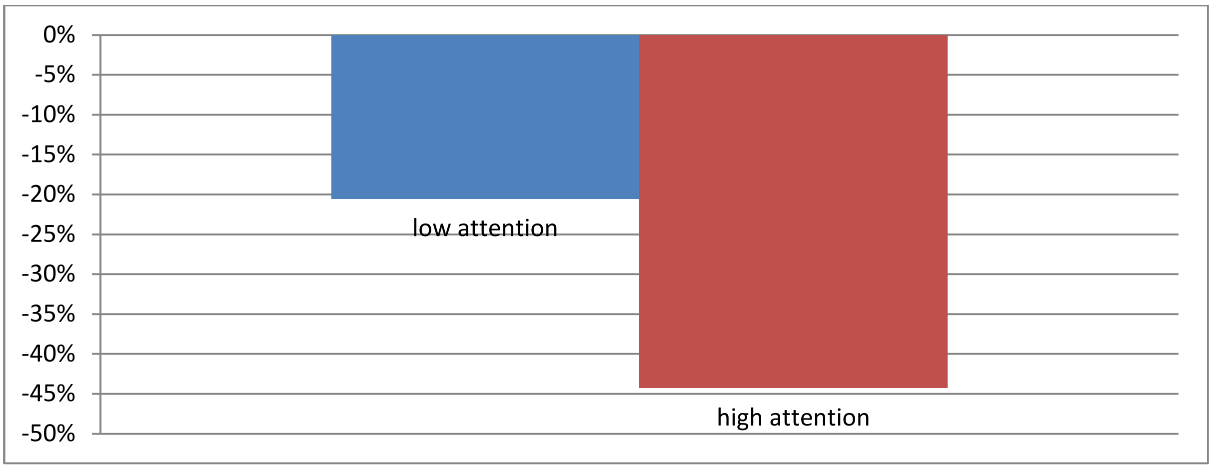
There is a significant upward trend in the attention level starting three days prior to spin-off day, and there is a significant jump (nearly 200 percent) during the day prior to the date of spin-off deal and the day of spin-off deal, reflecting a surge in public attention for the stock. Interestingly, the shift in attention is not permanent: the attention level reverts to its pre-spinoff level the day following the deal.
Third, we analyze the relation between change in investors' attention and spin-off returns, finding find that the set of spin-offs with low attention during the week prior to the deal have first-day returns of -0,40% on average, while the set of spin-offs with high attention have much lower first-day returns of -2,9% on average (Figure 3). The difference between the two average first-day returns is due to an increase in the spin-off with high attention returns higher than spin-off with low attention in the date of deal.

Figure 3. Attention level and percentage variation of spin-off returns after one day



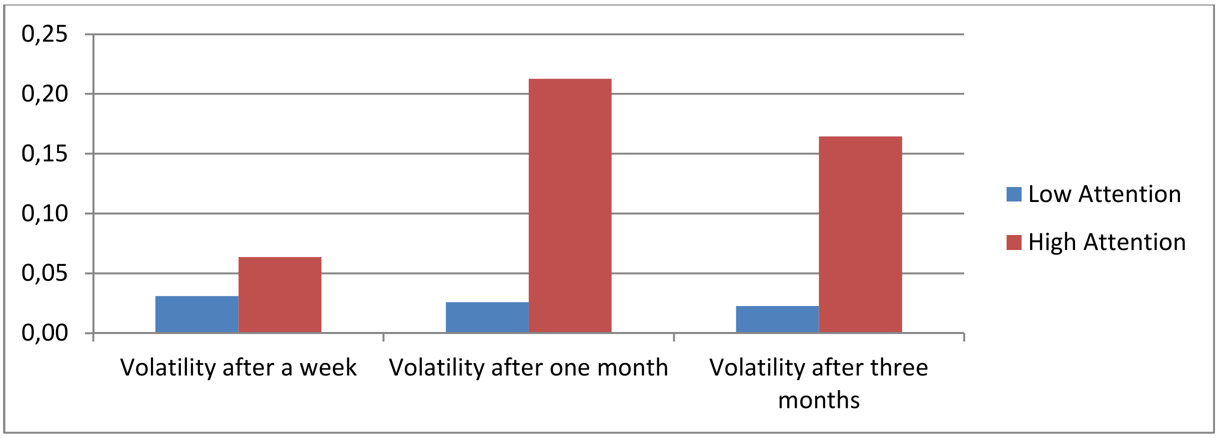
Fourth, the change in attention level has an impact also on trading volumes. In Figure 4, we observe a significant slump in the volumes of spin-off with high attention the day following the deal. The trading volumes of the set of spin-offs with high attention on the deal-date are higher than the trading volumes of the set of spin-offs with low attention, producing a greater fall the day following the deal.

Figure 4. Attention level and percentage variation in trading volumes after one day



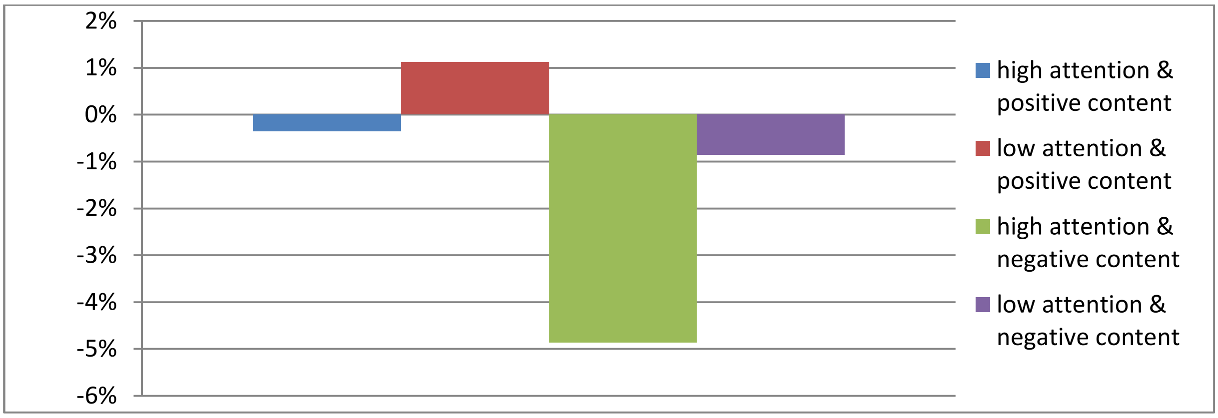
Fifth, we analyze the relation between investor attention and stocks volatility. Figure 5 displays that a week after the date of the deal, the volatility (at various dates) of spin-off stocks with high attention is higher than the volatility of the spin-off stocks with low attention.

Figure 5. Attention level in relation to volatility over the time horizon considered



Finally, Figure 6 shows that investor attention amplifies the effect of media sentiment on spin-off returns. The returns related to the spin-off with high attention and positive (negative) media sentiment have a higher positive (negative) reaction with respect to the set of the spin-off with low attention and positive (negative) media sentiment.

Figure 6. Media sentiment, change in attention indicator and percentage variation of spin-off returns after one day



3.2. Evidence from a dynamic model

In order to understand the dynamic interaction of the attention with other relevant variables we consider a dynamic model which includes the returns of the spin-offs (R), their variation in volumes traded on the market (V), the change in attention indicator (A) and the average returns of the market (D). All the variables regarding each spin-off refer to a period of three months from the deal date and are averaged.

This dynamic model is built as a sparse structural vector autoregression (SVAR). To build such a model we adopt an approach based on graphical modelling (Reale and Tunnicliffe Wilson, 2001).

This approach effectively identifies the relationship between the variables at time t, e.g. the current values of the time series; moreover it provides a sparse structure, where only the significant relationships between variables are considered. Its advantage is that it identifies such relationships without prior constraints. A SVAR model of order p, indicated as SVAR(p) con be written as

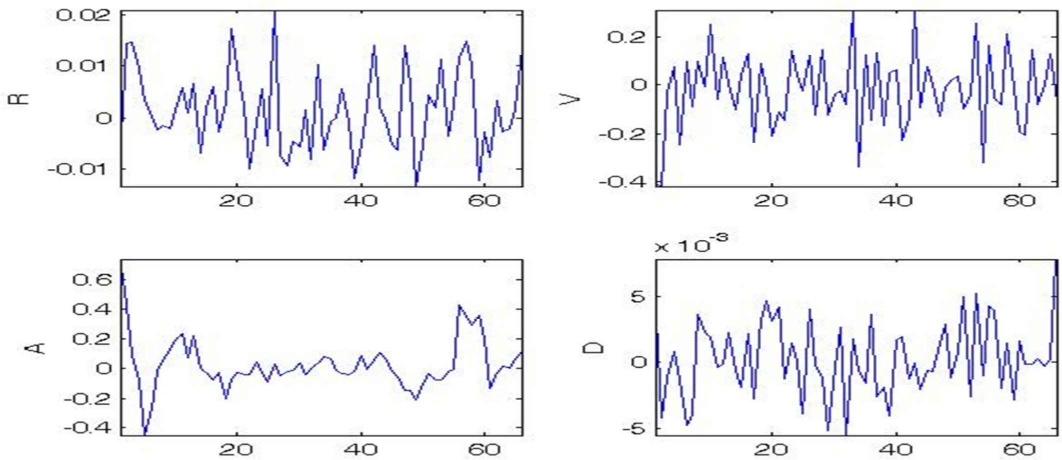
$$\Phi_0 x_t = \Phi_1 x_{t-1} + \Phi_2 x_{t-2} + \ldots + \Phi_p x_{t-p} + \varepsilon_t ;$$

where

$$x_{t-j} = [x_{1,t-j}, x_{2,t-j}, \ldots, x_{m,t-j}]^T \quad j=0,\ldots,p$$

is a vector of time series states at lag j, when $j=0$ we have the current states of the time series. In our case, a visual inspection of all our m=4 time series in Figure 7 suggests they are stationary, however the approach we follow would be valid even if the time series were *I(1)* independently from any cointegration (Tunnicliffe Wilson and Reale, 2008) although obviously the interpretation of the results would require more care in such a context.

Figure 7. Time plots of the variables considered in the dynamic model



The errors' vector

$$\varepsilon_t = [\varepsilon_{1,t}, \varepsilon_{2,t}, \ldots, \varepsilon_{m,t}]^T$$

is a multivariate white noise with general diagonal covariance matrix W. The working assumption is that the series are Gaussian but the method we apply is applicable under wider conditions, such as ε_t being I.I.D., presented for example in Anderson (1971).

This model is attractive because its estimation from a sample $x_{i,1}, x_{i,2}, \ldots, x_{i,n}$ with $i=1,\ldots,m$, by least squares applied separately to each component $x_{i,t}$ of x_t is straightforward. The properties of the estimates given by the regression are reliable, and the estimate of W is independent of the estimates of Φ_j, the matrices of the coefficients of x_{t-j}. The approach we follow will lead to sparse identification and estimation of all these matrices, including Φ_0.

There are various approaches to multiple time series modelling which seek either to transform models such as a vector autoregression (VAR) to a form which includes contemporaneous relationships among the variables, or to identify directly such a form, see for example Box and Tiao (1977) and Tiao and Tsay (1989).

Our approach in this paper is similar: we consider the structural autoregressive model of the same form as a VAR but with the addition of contemporaneous dependence through the coefficient matrix coefficient Φ_0. We require this matrix to represent a recursive (causal) dependence of each component of x_t on the others. This is equivalent to the existence of a re-ordering of the elements of x_t such that Φ_0 is triangular with unit diagonal.

The first step in the specification of our model is the identification of the order *p* of the SVAR. This identification can be done by various methods, including the inspection of the multivariate partial autocorrelation functions (Reinsel, 1993) or by the minimization of an order selection criterion such as AIC (Akaike, 1973), CAIC (Hurvich and Tsai, 1989), HIC (Hannan and Quinn, 1979) and SIC (Schwarz, 1978). Table 2 provides the order selected by the different criteria for a SVAR containing our four variables.

Table 2. SVAR order identified by different information criteria

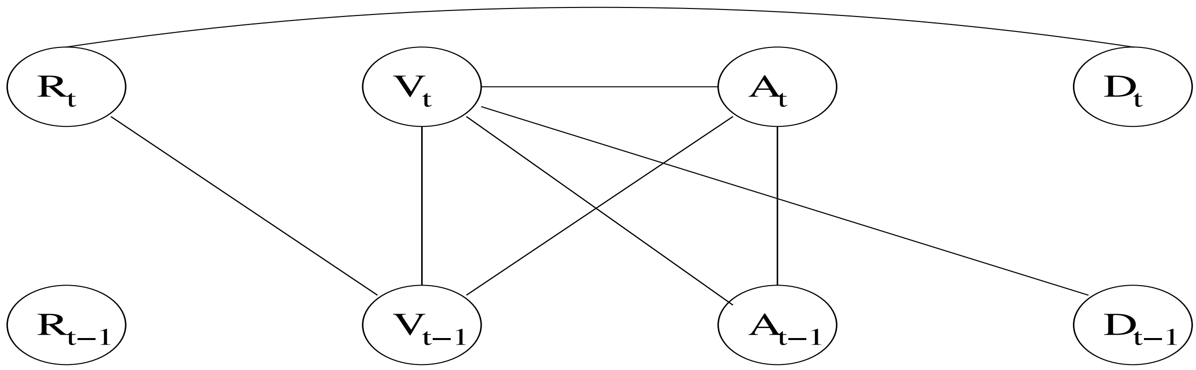
AIC	**CAIC**	**HIC**	**SIC**
1	4	1	1

We opted for the order *p=1,* suggested by AIC, HIC and SIC, that leads to the model involving eight variables (R, V, A and D at time *t* and at time *t-1*). We then use pair-wise sample partial correlations, conditioning on all remaining variables, to construct the conditional independence graph (CIG) of the eight variables, following procedures presented for example in Edwards (2000). As Swanson and Granger (1997) remark, the structural form of dependence between the variables is naturally expressed by (and is equivalent to) a directed acyclic graph (DAG), in which nodes representing variables are linked with arrows (directed edges) indicating the direction of any causal dependence. A DAG implies a single CIG for the variables, but the possible DAG's which might explain a particular CIG may be several or none. The point is that, subject to sampling variability, the CIG is a constructible quantity and a useful one for expressing the data determined constraints on permissible DAG interpretations.

The CIG consists of nodes representing the variables, two nodes being without an edge if and only if they are independent, conditional upon all the remaining variables. In a Gaussian context this conditional independence is indicated by a zero partial correlation.

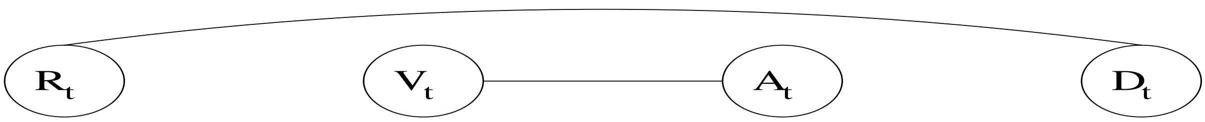
In the wider linear least squares context, defining linear partial correlations as the same function of linear unconditional correlations as in the Gaussian context, still usefully indicates lack of linear predictability of one variable by the other given the inclusion of all remaining variables. We tested the significance of the partial correlations representing the edges (relationships) at a type 1 error probability threshold of 0.05. The resulting CIG is presented in Figure 8.

Figure 8. Conditional Independence Graph for the variables in a SVAR(1)



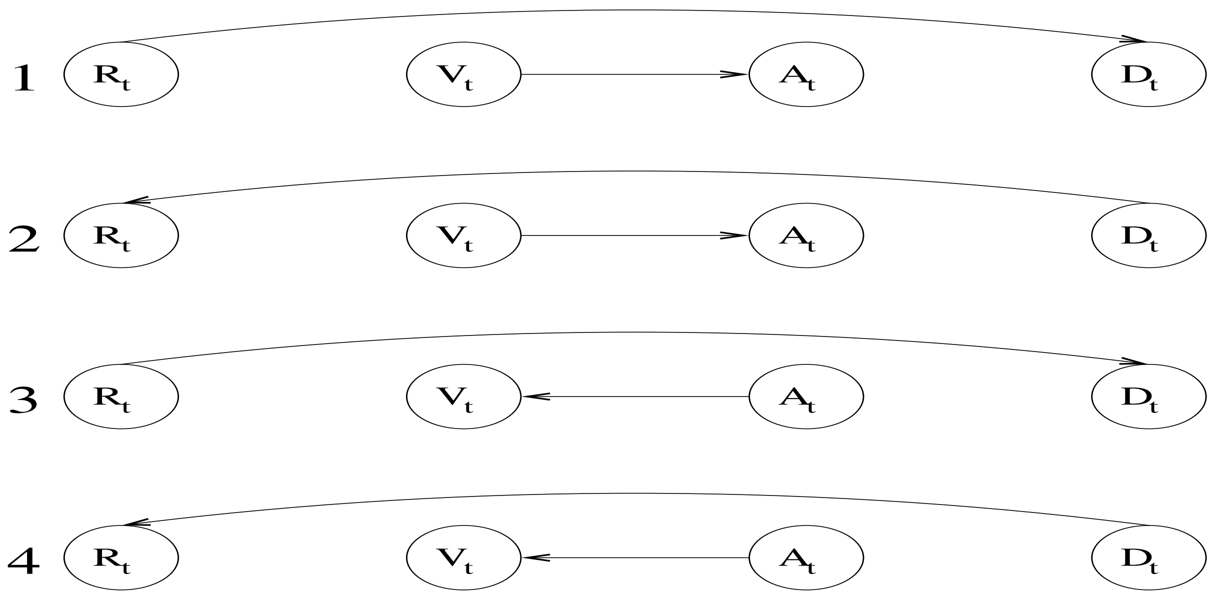
The CIG considers only edges linking to current variables, as we are interested in specifying a model for x_t. However, using the appropriate sample properties (Reale and Tunnicliffe Wilson, 2002), we could also test for significant edges between lagged variables. This sometimes could be useful even in the identification of a model for just x_t. As we have already mentioned, there are several possible DAG's that can explain a CIG, so we need now to identify the more likely DAG of the several possible ones consistent with CIG we obtained from the data. This practically resolves into finding the more likely direction of the edges that so far are undirected. In this task the flow of time comes to our help and we can reasonably assume the direction from lagged variables to the current ones. Hence we just need to concentrate on possible links between current variables. The sub-graph of the CIG considering the edges between the current variables is illustrated in Figure 9.

Figure 9. Sub-graph of the CIG including just the current variables



Considering the sub-graph we can think of four possible DAG's, illustrated in Figure 10, leading to four different models named model 1, model 2, model 3 and model 4.

Figure 10. All the possible DAG's explaining the CIG between current variables



We are now left with the decision to choose one of the four possible models; at this stage both financial theory and statistical evidence can guide us. From the statistical point of view we can use penalized likelihood selection criteria, like the ones used to select the SVAR order, for this choice.

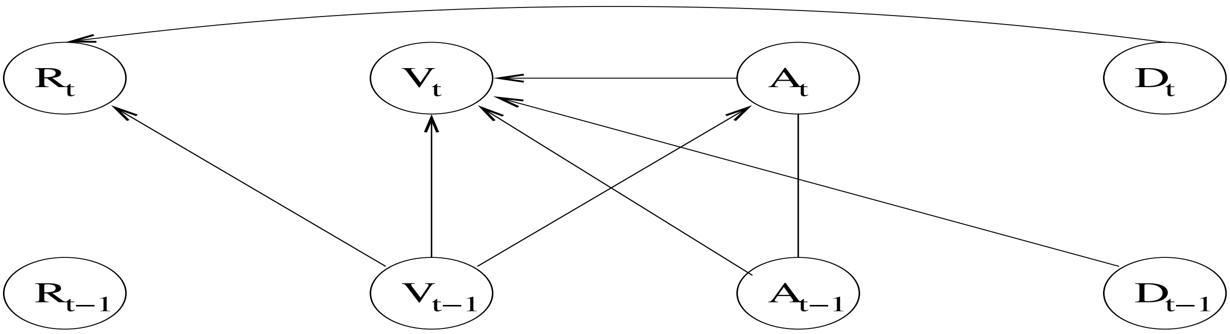
In Table 3 we report the number of parameters and the values of AIC, HIC and SIC for the four models and also for the saturated model, which is the model with non-zero coefficients as a control. The direction of the edges in the saturated model is irrelevant as all the different models with different non-cyclical direction of the edges have the same likelihood. At this stage we could operate further simplification by subset regression excluding non significant parameters for the four models initially selected, but in our case all the parameters were significant and no further simplification could be done.

Table 3. Number of parameters and values of information criteria for the different models

Model	Parameters	AIC	HIC	SIC
1	8	-1961	-1954,1	-1943,6
2	8	-1962,5	-1955,6	-1945,1
3	8	-1962,7	-1955,8	-1945,3
4	8	-1964,2	-1957,3	-1946,8
Saturated	22	-1950,9	-1932	-1903

A first observation arising from an analysis of the results reported by the table is that all 4 models perform better than the saturated model; second, all the different selection criteria, that have a different penalization for the number of parameters, give the same order of preference for the four models as they have the same number of parameters; the last observation is that model number 4 is the best model from the statistical point of view but it is also convincing from financial theory point of view. The DAG for model 4 is shown in Figure 11.

Figure 11. DAG of model 4



We eventually can describe this model with a system of three equations, as D_t results as exogenous, providing both coefficients and the corresponding *t-values* in round brackets. The equations are:

$$R_t = 0{,}0015 + \underset{(4{,}0949)}{1{,}2817}\, D_t - \underset{(-1{,}8837)}{0{,}0103}\, V_{t-1}$$

$$V_t = -0{,}0231 + \underset{(2{,}7329)}{0{,}3944}\, A_t - \underset{(-3{,}1870)}{0{,}3295}\, V_{t-1} - \underset{(-3{,}2846)}{0{,}4152}\, A_{t-1} - \underset{(-3{,}8197)}{22{,}4956}\, D_{t-1}$$

$$A_t = 0{,}0278 + \underset{(2{,}1305)}{0{,}1840}\, V_{t-1} + \underset{(7{,}6993)}{0{,}6096}\, A_{t-1}$$

According to the model, the stock market returns (D_t) and the lagged volumes (V_{t-1}) are significantly related to current-day spin-off returns (R_t). However, the relation between the lagged volumes and the current-day spin-off returns is negative, because generally the returns react to the trading volumes at the same time. However since high volumes show that investors are interested in both buying and selling a stock, we cannot confirm the Barber and Odean's (2008) conjecture that individual investors are net buyers of attention-grabbing stocks.

The current-day spin-off volumes (V_t) are significantly and positively affected by the current-day attention indicator (A_t): this is consistent with the hypothesis that an increased attention level, due to a spin-off deal, has a contemporaneous effect on the trading volumes, enhancing them. On the other hand both the lagged volumes (Vt-1) and the lagged attention indicator (At-1) have a negative impact on current-day volumes: a growth of Google searches, as a proxy of the attention level, involves an increase of trading volumes thus reducing the spin-off returns of the following day. This may well be consistent with the framework of Daniel, Hirshleifer and Subrahmanyam (1998) in which high attention results in downward pressure on stock market returns. The lagged stock market returns (Dt-1) also negatively affect the current-day spin-off volumes.

Finally, we find that the lagged volumes (V_{t-1}) and the lagged attention indicator (A_{t-1}) significantly and positively affect the current-day attention indicator (A_t). The investors may start to pay attention to a stock and search it in Google the day previous to the spin-off date, leading to a significant jump in attention level on the deal day: we observe that individual investors' attention is grabbed by stocks experiencing high trading volumes on the previous day.

4. Conclusions

This paper investigates empirically the nature of the interactions between mass media, investor attention and the stock market. In particular we provide some preliminary evidence about the impact of media-provided information and the level of investor attention in spin-off deals market.

The contribution of this study is manifold. First of all, our results show the existence of a significant upward trend in the attention level starting three days prior to spin-off day and a significant jump during the day of the spin-off deals.

Subsequently, our findings support the general argument that the characteristics of information provided by mass media influence investor choices about spin-off firms. In this perspective, we evidence that mass media information is important not only for its novelty, but also for its effects on investor sentiment. As one could expect, media sentiment, measured as semantic content of the news, influences the investors' preferences and therefore returns around the spin-off deals date. In particular a positive (negative) media sentiment in news spread before spin-off deals is associated with positive (negative) short term returns.

We find also that an increase in investor attention determines an increase of trading volumes and volatility of spin-off firms in both the short and the long run. Nevertheless, results show that investor attention enhances / moderates the effect of media sentiment: the returns related to the spin-off with high attention and positive (negative) media sentiment have a higher positive (negative) reaction with respect to the set of the spin-off with low attention and positive (negative) media sentiment.

Finally, results of our dynamic model show that an increased attention level, due to spin-off deals, has a contemporary effect on the trading volumes, enhancing them. In addition, we observe that individual investors' attention is grabbed by stocks experiencing high trading volumes in the previous day. However since high volumes show that investors are interested in both buying and selling a stock, we cannot confirm the Barber and Odean's (2008) conjecture that individual investors are net buyers of attention-grabbing stocks. Besides, results seem to be consistent with the theoretical framework of Daniel, Hirshleifer and Subrahmanyam (1998) in which high attention results in downward pressure on stock market returns and volumes.

We are aware that differences in relative levels of expertise, risk, and other types of investment preferences of different types of investors may exert a role in different ways. Therefore, a challenge for future research is to comprehend if, and under what conditions, the characteristics of the investors influence information use and processing.

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