Investigation of the impact of financial communication intensity on the conditional volatility of stock returns

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ABSTRACT

The relationship between information flow and asset prices behaviour is one of the key issues of modern finance. Our study investigates more closely the relationship between frequency of information arrivals and stock return volatility. Our study aims precisely to test empirically the mixture of distribution hypothesis and to check whether the stock returns distribution is driven by the frequencies of information arrivals on the Paris stock Exchange (Euronext). We analyse the impact of news on volatility at the firm-level. We opt for a model with two (Markov switching) regimes of volatility that we apply to all stocks pertaining to the CAC40 index from January 1999 to December 2003. We find a positive and significant impact of the daily frequency of information arrivals on the probability to be in a state of high volatility for each of the 48 companies considered. This result is confirmed by the subsequent model for panel data.

JEL codes: G14,

Keywords: News,(conditional)Volatility, Public information arrival, Mixture of distribution hypothesis, Communication intensity, Markov Switching Regression Model

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1. Introduction

The relationship between information flow and asset prices behaviour is one of the key issues of modern finance. How, why and under which conditions do financial news impact stock price volatility count among the typical (and still debatable) questions in this research area. The clear knowledge and the good understanding of such important issues are of first importance for listed companies The behaviour of stock prices around profit warning announcements is a typical (and probably extreme) example of these phenomena. A brief and quick look at the Wall Street Journal is sufficient to gain some insight. On Sept. 20, UTStarcom said it expected to earn two cents to four cents (per share) for the third quarter, down sharply from an earlier forecast of 34 cents to 35 cents. As a consequence, shares of the company lost 10% in one day, with a trading volume eight times higher than its historical average[1]. A few days later, on September 24, the same kind of announcement from the UK telecommunications company Thus Group PLC involved yet more damaging effects. As a result of an expected EBITDA lower than initially forecast, Thus shares tumbled 25% to 12.75 pence as the stock exchange opened. Moreover, sector spill over effects of such announcements have been quite common. On September 16, after Celestica, a large-cap electronics manufacturer, cut its outlook for the third quarter, the whole sector of makers of electric parts and equipment as well as providers of related services dropped: Power-One tumbled 6.4%, Plexus fell 5.4%, Littlefuse shed 3.3% and Benchmark Electronics lost 10% on the New York Stock Exchange. The communications-technology sector was affected the same way, since Stratex Networks dropped 4.4%, Mindspeed Technologies lost 3.3% and MRV Communications fell 3.2%. Financial communication may thus strongly impact stock return, volume and volatility of any company. Such a point deserves to be studied and analysed with the highest attention.

[1] From a WSJ article of Shira Ovide on September 29.

And it has been the case. The scientific community has accumulated a large amount of evidence in this field. The well-known efficiency tests of Fama (1970) count among the fundamental on this topic. They aimed at testing whether prices reflect (market, public or private) information accurately and concluded that the weak and semi-strong form efficiency hypothesis could not be rejected. As a consequence, by assuming market efficiency, event studies (see Beaver (1968) and FFJR (1969) for example) could develop and estimate the impact of specific events (like stock splits, or mergers and acquisitions) on stock returns. Through an original and interesting study of the frozen orange juice market, Roll (1984) found a statistically significant relation between orange juice returns and subsequent errors in temperature forecasts issued by the National Weather Service, although he admitted there still remains a large amount of inexplicable price volatility. After some debate and discussion about the information incorporation into stock prices, researchers tackled soon the issue of *how fast* information incorporates into stock prices. In that prospect, Chordia and al. (2001) bring new evidence on the speed of convergence to market efficiency. They show that it takes at most thirty minutes for investors on the NYSE to make prices unpredictable.

If some researchers proved much interest in the issue of the incorporation of information into stock prices, others chose to focus on the impact of information on stock return volatility. Our own study, by investigating more closely the relationships between frequency of information arrivals and stock return volatility, finds its place in this latter stream of works that will be discussed in detail below.

Recent academic works have put into light the importance of developing a better understanding of the determinants of return volatility. Easley and O'Hara (2001) bring some evidence that the less transparent and disclosing a company is, the higher its cost of capital will be. Such a conclusion already offers some insight of how significant the influence of news releases (in quality and in quantity) on stock prices can be. Campbell and al. (2001) find that the proportion of firm-specific variance in the total stock variance has steadily been increasing for the last thirty years and thus provides us with another good reason to investigate the relationship between firm-specific news and idiosyncratic volatility. As a matter of fact, one may wonder whether the regular increase in idiosyncratic variance detected by Campbell and al. (2001) could possibly be linked with the obvious contemporaneous increase in the financial communication intensity. Our results seem to support such an assertion. Eventually, Goyal and Santa Clara (2002) detects a positive relationship between idiosyncratic variance and expected stock return. For idiosyncratic risk is not perfectly diversifiable and investors are assumed risk-averse, an increase in the firm-specific part of the stock volatility can induce an increase in the cost of capital[2].

The link between the volatility of stock prices and the information arrival intensity has already been pointed out in previous contributions, at least from a theoretical point of view. The mixture of distribution hypothesis (MDH) counts among the most popular of them and was suggested for the first time by Clark (1973). It posits that the joint distribution of daily return and volume can be modelled as a mixture of bivariate normal distributions. Specifically, they are contemporaneously dependent on an underlying mixing variable that represents the flow of information. As a consequence, the variance of returns at a given interval is expected to be proportional to the rate of information arrival at the market. About sixteen years later, Ross (1989) brings theoretical evidence that in an arbitrage-free economy, the volatility of prices is directly related to the rate of flow of information to the market. Our study aims precisely to test empirically this mixture of distribution hypothesis and to check whether the stock returns distribution is driven by the frequencies of information arrivals on the Paris stock Exchange (Euronext).

Despite the above mentioned theoretical contributions, the empirical evidence of the positive relation between frequency of news arrivals and stock volatility is everything but overwhelming, probably because of the difficulty to find empirical proxy of information

[2] However, this point remains controversial. In obvious contradiction with Goyal and Santa Clara (2002), Wei and Zhang (2004) claim that idiosyncratic risk does not matter.

arrivals and as a result of the lack of high frequency data up to the end of the eighties. The difficulty to precisely measure information arrivals appears in the variety of proxies used by the previous empirical studies on the topic. Berry and Howe (1993) use the number of daily newspaper headlines and earnings announcements and Ederington and Lee (1993) investigate the importance of macroeconomic news, whereas Mitchell and Mulherin (1994) employ the number of specific stock market announcements in order to test the impact of the rate of information on the market volatility. « However, the use of unconditional volatility measures such as absolute daily market returns in these studies often generates weak or inconclusive results regarding the news–volatility relation. Such findings are likely to be due to the presence of conditional heteroscedasticity, which is well documented in most financial time-series. »[3]. In order to account for this well-known phenomenon of conditional heteroscedasticity, Kalev and al. (2004) choose to test the relation between firm-specific announcements (as a proxy for information flows) and volatility on the Australian Stock Exchange in a GARCH framework. Their analysis reveals a positive and significant impact of the arrival rate of the selected news variable on the conditional variance of stock returns, even after controlling for the potential effects of trading volume and high opening volatility. However, although ARCH-type models are useful and efficient empirical tools, they cannot provide a sound theoretical explanation for the obvious volatility persistence phenomenon and for the exact contribution of information flows in the volatility-generating process. In addition, they say nothing about the underlying determinants of the volatility. According to Kalev and al. (2004), an appealing answer to these issues could be inferred from the Mixture of Distribution Hypothesis already defined above, which basically consists in modelling the overall stochastic process of price changes with a mixture of probability models, i.e., a different probability distribution during news and non-news periods. Consistently with Roll (1987), sample variance and kurtosis for example can reveal something about the probability

[3] Kalev et al. (2004), p. 1442

of information and the difference between the information-related distribution and the non-information-related distribution of returns[4].

In order to test empirically whether information flows drive stock return volatility, we apply our econometrical model to all stocks pertaining to the CAC40 index from January 1999 to December 2003. Datastream provides us with the series of daily stock prices, while all financial and industrial Reuters news concerning the companies selected above are retrieved from Factiva on-line. Since we were only interested in the impact of information intensity on the idiosyncratic stock variance, we restricted our investigation to firm-specific and industrial-specific news and chose not to introduce any market or macroeconomic news in the sample (as it will be explained below, we will control for market effects on idiosyncratic stock variance through controlling for the market variance in the regression equation).

Our methodology differs in many respects from the above mentioned previous studies on the topic. We analyse the impact of news on volatility at the firm-level, i.e. company by company, and not at the market-level, i.e. impact of news on the index. It allows us to capture the entire "firm-specific effect" contained in the news which is obviously lost at the aggregate level. We also employ conditional volatility measures (instead of unconditional volatility measures) in order to take the volatility persistence into account. We opt for a model with two (markov switching) regimes of volatility, which is more robust and general than the GARCH model used by Kalev and al. (2004) because it needs less strong assumptions on the conditional volatility process (no linearity hypothesis for example). Moreover, such a Markov switching regimes model allows us to explicitly take advantage of the central Roll (1987)'s idea[5] of a mixed return distribution ("with news" and "no news") driven by news arrivals and to test the relevance of such an intuition. The econometrical methodology consists basically in two steps: estimating the daily probabilities of being in a high volatility state thanks to the developed Markov switching regimes model and regressing these obtained probabilities on

[4] Roll (1988).
[5] The MDH in fact.

some possibly explicative variables in order to understand the determinants driving the stock returns volatility. Unlike Kalev and al. (2004), we control for factors such as the market conditional volatility and the sector conditional volatility, the latest being certainly a key feature of our work. Eventually, we find a positive and significant impact of the daily frequency of information arrivals on the probability to be in a state of high volatility for each of the 48 companies considered. This result is confirmed by the subsequent model for panel data.

Our paper is organized as follows. Section 2 presents the Markov switching regimes model. Section 3 describes the used data sets: stock prices and news. Section 4 displays and comments results. Section 5 concludes and provides some perspectives for future research.

2. The model

The way that we propose to model the stock's variance behavior is in line with the MDH and Roll's (1987) results. According to Roll, the true return generating process seems to be better described by a mixture of two distributions: one corresponding to a state of information arrival, and the other to the normal return behavior. In order to study the impact of news on volatility at the firm level, our approach is based on a combination of the well-established market model (Sharpe, 1963) and the more recent Markov Switching Regression models (MSR), largely introduced and developed by Hamilton (1989 and 1994), and significantly extended in Krolzig (1997). Our initial intuition is simple: if the occurrence of firm-specific events may have a significant impact on the variance of the firm's return generating process, we must capture this perturbation using a regime switching model.

The two-state market model

Now, we assume that the residual is state dependent. S_t denotes our state variable. We consider the case of a two-state regime model (mixture of two distributions with different variances). More precisely, we have a low-variance regime ($S_t=1$) and a high-variance regime ($S_t=2$):

$$\begin{aligned} y &= X\delta + \varepsilon_1 \quad if\, S_t = 1 \\ y &= X\delta + \varepsilon_2 \quad if\, S_t = 2 \end{aligned}. \tag{1}$$

The variance of the residuals for each state is given by:

$$\begin{aligned} E[\varepsilon_1 \varepsilon_1' | X] &= \sigma_1^2 I \quad if\, S_t = 1 \\ E[\varepsilon_2 \varepsilon_2' | X] &= \sigma_2^2 I \quad if\, S_t = 2 \end{aligned}, \tag{2}$$

where $\sigma_2^2 > \sigma_1^2$.

We assume that the transition between the two regimes is governed by a Markov chain of order 1, for which the transition matrix is given by:

$$P = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix}, \tag{3}$$

where $p_{ij}=p(S_t=i|S_{t-1}=j)$ corresponds to the probability of going from state j to state i. The unconditional probability of the regime is given by (Hamilton, 1994, p. 683):

$$\begin{aligned} p(S_t = 1) &= \frac{1 - p_{22}}{2 - p_{11} - p_{22}} \\ p(S_t = 2) &= \frac{1 - p_{11}}{2 - p_{11} - p_{22}} \end{aligned}. \tag{4}$$

The intuition underpinning our choice is simple: we anticipate that firm-specific events will impact the return variance. It could be argued that it is in contradiction with the semi-strong form of efficiency hypothesis, under which the prices should adjust immediately to any public information announcement. It is in fact not the case if we take into account the uncertainty attached to firm-specific events. We will suppose that the return generating process can be adequately modeled using a two-regime process[6], one regime with normal variance and one regime with high variance (firm-specific event regime). Note that, in both regimes, the MM (market model) parameters are assumed to be the same. Therefore the return generating process is:

$$\begin{aligned}
&R_{j,t} = \alpha_j + \beta_j R_{m,t} + \varepsilon_{j,1,t} \quad \text{if } \mathrm{S_t} = 1 \text{ with } \varepsilon_{j,1,t} \sim \mathrm{N}(0, \sigma_{\mathrm{j,1}}) \\
&R_{j,t} = \alpha_j + \beta_j R_{m,t} + \varepsilon_{j,2,t} \quad \text{if } \mathrm{S_t} = 2 \text{ with } \varepsilon_{j,2,t} \sim \mathrm{N}(0, \sigma_{\mathrm{j,2}}) \;, \\
&\text{and} \quad \sigma_{\mathrm{j,2}} > \sigma_{\mathrm{j,1}}
\end{aligned} \tag{5}$$

where S_t is a state variable taking value 1 if we are in the low variance regime and 2 if we are in the high variance regime. In the sequel, we will refer to equation (5) as the two-state market model (TSMM). The proposed model is a direct and parsimonious extension of the classical MM. As the regime state variable S_t is not directly observable, we have to specify its statistical properties. The model we propose is therefore based on the estimation of six parameters (α, β, σ_1, σ_2, p_{11} and p_{22}) and, while much more flexible than the classical MM model, remains parsimonious.

The estimation of Markov Switching Regression models is fully presented in Hamilton (1994). It is based on a maximum likelihood approach, for which an efficient estimation algorithm has been developed. The estimated probability of being in a specific state at a specific date is one of the interesting by-products of the advocated approach. It allows one to look for the reasons explaining an increase in variance: in our case, look for the link between information flow and conditional variance.

The use of this Markov Switching Regression model provides numerous interesting features. Beyond the above-quoted possibility of obtaining the estimated probability of being in a specific regime at a specific date, this specification is in line with Roll's (1987) intuition. In his Presidential Address to the American Finance Association, he clearly highlighted that

[6] This hypothesis is supported by unreported results. Using the approach developed in Krolzig (1997), we find that a two-regime model is an adequate representation of the return generating process in the vast majority of cases. Three-regime decomposition appears to be justified only in the presence of strong outliers.

the true return-generating process seems to be better described by a mixture of two distributions, the first one corresponding to a state of information arrival and the other to the normal return behavior: it's clearly a good candidate for testing the mixture of distribution hypothesis. Once we have estimated the probability for a firm of being in a high variance regime at a specific date, we can test whether it is linked with information flow.

The specification has other attractive features:

- the Gaussian conditional distribution of returns could be misleading. While the model imposes a Gaussian assumption for the return distribution in each state, as shown in Hamilton (1994) and Krolzig (1997), it allows to capture skewness and kurtosis in the unconditional distribution;
- the Markov Switching Regression framework also takes conditional heteroscedasticity into account without imposing a specific form on the conditional dependence of the variance (as in the (G)ARCH framework);
- finally, the estimation process provides us with the estimated variance in each regime, the probability of being in a specific regime at a specific date, and the estimated transition probabilities[7].

3. The data

Our firms' universe is composed of the CAC40 index stocks (or: All firms considered pertain to the CAC40 index). It provides us with a broad and representative sample of the French Stock Market, accounting for 70% of the French stock market value. The total market value of the index on November 11, 2003 was € 722 billions. The mean (median) company market value was € 18 billions (€ 13 billions). For all the firms included in this index, we use

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[7] All estimations presented in this paper have been realized under the Ox econometric software, using the Krolzig MSVAR package. We thank Professor J. Hamilton for advising the use of this package. It is freely downloadbale at: http://www.nuff.ox.ac.uk/Users/Doornik/index.html.

daily prices from January 1, 1999 to December 31, 2003. The three largest sectors in the index were the financials (22.29%), resources (oil) (18.27 %) and non cyclical consumers' goods (11.82%). We use as a market portfolio the CAC40 index. The data are obtained from Datastream, accessed at the Université de Lille 2.

Our news sample is provided by Factiva. It is composed of all corporate and industrial news concerning firms pertaining to the CAC40 index and recorded by Reuters from January 1, 1999 to December 31, 2003. For each news, we have got the following fields: the accession number (AN), headline (HD), word count (WC), publication date (PD) and time (ET), source name (SN) and code descriptor (SC), lead paragraph (LP), company (concerned by the news) code (CO), industry code (IN), subject code (NS), region code (RE), Dow Jones codes (DJIC) and descriptors (DJID), information provider codes (IPC) and Reuters codes (RBBCM). One news can of course concern several companies, industries and subjects.

To avoid any redundancy and duplicate news that do not bring any additional information value, we restrict the sample to the news released by Reuters only. For the same reason, we eliminate all the news with same headlines and lead paragraphs. Eventually, after having excluded news with one missing field or more, we are left with 76341 financial communications over the whole five-year-period.

Fields like company, industry and subject deserve to be examined in detail.

There are 56 different companies in the sample (each of them appeared at least once in the CAC40 index over the selected sample period). In 2001, figure 1 shows that news releases intensity was the highest for Vivendi Universal (14.4%), France Telecom SA (14.1%), Renault SA (9.1%), Alcatel SA (8.7%) and Aventis SA (7.4%).

Concerning industry sectors, they are split into ten general categories and 56 sub-categories. Figure 2 shows that the three sectors with highest news frequency in 2001 were

“Metal, Goods and Engineering” (48.6%), “Financial and Business Services” (43.7%) and “Transport and Communication” (37.6%)[8].

Subjects have also been divided into 5 general categories and 105 more specific ones. From figure 3 one can observe that the 6 most common news subjects are performance (24.5%), ownership changes (23.2%), acquisitions/mergers/takeovers (20.8%), equity markets (20.1%), earnings projections (17.2%) and earnings (12.1%).

4. The results : news impact on variance level

4.1 Securities analysis

At this point, we could use a probit regression or directly the estimated probability of being in a specific state. For the last, we have to take into account the inherent heteroscedastic nature of our regression models in order to build correct inferences. We follow the procedure presented in appendix , leading us to use as dependent variable the logistic transform of the estimated probability.

Probit regression

For this case, we transform the state regime into a dummy variable $D_{i,d}$, equal to 1 when the probability of being in the high variance regime at a specific date d is superior to 50% and 0 otherwise.

(24) $$D_{i,d}=\beta_{i,0}+\beta_{i,1}N_{i,d}+\sum_{j=2}^{J+1}\beta_{i,j}\times X_{i,j,d}+\eta_{i,d}$$

where i and d represent respectively the security i and the day d ;

$D_{i,d}$ = 1 if $P[S_{i,d}=2]\geq 50\%$ (« high variance regime »)

0 otherwise (« low variance regime ») ;

$N_{i,d}$ stands for the number of news specific to the security i on the day d;

$X_{i,j,d}$ stands for the j^{th} control variable.

[8] Percentages do not sum up to 100%, because one news release often concern more than one company, industry or subject. It follows that categories are not exclusive (but they are exhaustive).

OLS regression for proportion data

For the regression where the dependant variable equals the estimated probability of being in the state of high variance, the regression is:

$$P\left[S_{i,d}=2\right]=\beta_{i,0}+\beta_{i,1}N_{i,d}+\sum_{j=2}^{J+1}\beta_{i,j}\times X_{i,j,d}+\eta_{i,d} \qquad (25)$$

4.2 panel-data analysis

The advantage of the panel analysis is to take the global results into account: we analyze the combination of time and cross-sectional effects. Modeling in this setting calls for some complex stochastic specification. We therefore use the most common techniques: fixed effects and random effects.

The fixed effect approach takes the constant model to be a group-specific term in the regression model. The constant is different for any security. It should be noted that the term “fixed” as used here indicates that the constant term does not vary over time.

The random effects approach specifies that the residual is a group specific random element. In this model, the constant is the same for all the securities included in the sample.

The crucial distinction between these two cases is whether the unobserved individual effect embodies elements that are correlated with the regressors in the model, not whether this effect is stochastic or not. In our case, the fixed effect is better specified.

Control variables

We must include control variables in our regression to test the robustness of the impact of the specific news on the conditional variance of the security.

We choose the conditional variance of the market portfolio and the conditional variance of the sector index, both estimated by a GARCH framework, for controls variable. We test also the daily volume but the result is not significant. Consequently, this variable was not included in the table.

4.3 Results

4.3.1 Individual analysis

Probit Regression

Table 1 gives the results for the probit regression described above. For the 48 securities studied, 45 have a significant positive sign for $N_{i,d}$. This result shows that the number of security-specific news has an impact on the conditional variance regime. Trading days during which the security-specific news are important, seem to be in the high variance regime. The control variable has also a significant positive impact. This contributes to the robustness of our results.

OLS regression results

Table 2 gives the result for the OLS regression. The results are similar: the probability of being in the high variance state increases with the level of specific-news arrivals on this day. The results are more significant : the number of news coefficient is significant and positive for the 48 securities studied.

4.3.2 Panel results

The table 3 presents the results for fixed effect and random effect panel approach. As control variable, we add the conditional variance of the sector index for each security. Both approaches give similar results : the coefficients are positive and significant. The heterogeneity inter-security observed in the individual regression lets us think that the fixed effect approach fits better.

The main conclusion is that the specific news level clearly influences the conditional variance of returns.

5. Conclusion

Without a shadow of doubt, research works aiming at accurately identifying and understanding the link between information diffusion and stock prices are of prime importance and interest, as much for the academic world as it is for business corporations. In this general context, the main objective of our study is to investigate the impact of the news arrivals intensity on stock prices volatility. We use daily prices and Reuters releases concerning all stocks pertaining to the CAC40 index over the period ranging from January 1, 1999 to December, 31 2003. We apply the data a Markov switching regression model in order to determine the daily probability of the volatility regime to be in a high level state or a low level state. We find for each stock a positive and (5%-)significant relationship between the daily number of news and the daily probability of being in a high volatility state. The panel analysis confirms these results since the above detected positive relationship remains highly significant, even when controlling for the volume, for the sector variance and for the market variance. The daily number of news alone explains not less than 14% of the probability of being in a high variance regime.

A positive and significant relationship between news arrivals intensity and stock prices volatility seems thus to be reasonable and consistent. Hence it follows that news contain some relevant and valuable information to the market, since these news have just been proved to significantly impact the stock return distribution. Such a finding is consistent with Roll's idea (and others before him) that the stock return distribution would be different whether we are in a "no-news" or a "with-news" period.

Now that the link between news frequency and stock price volatility is quite ascertained, future research could be extended in order take the informational content of the news into account. It could be done through distinguishing between “good” and “bad” news, between their subjects and such other features.

Figure 1

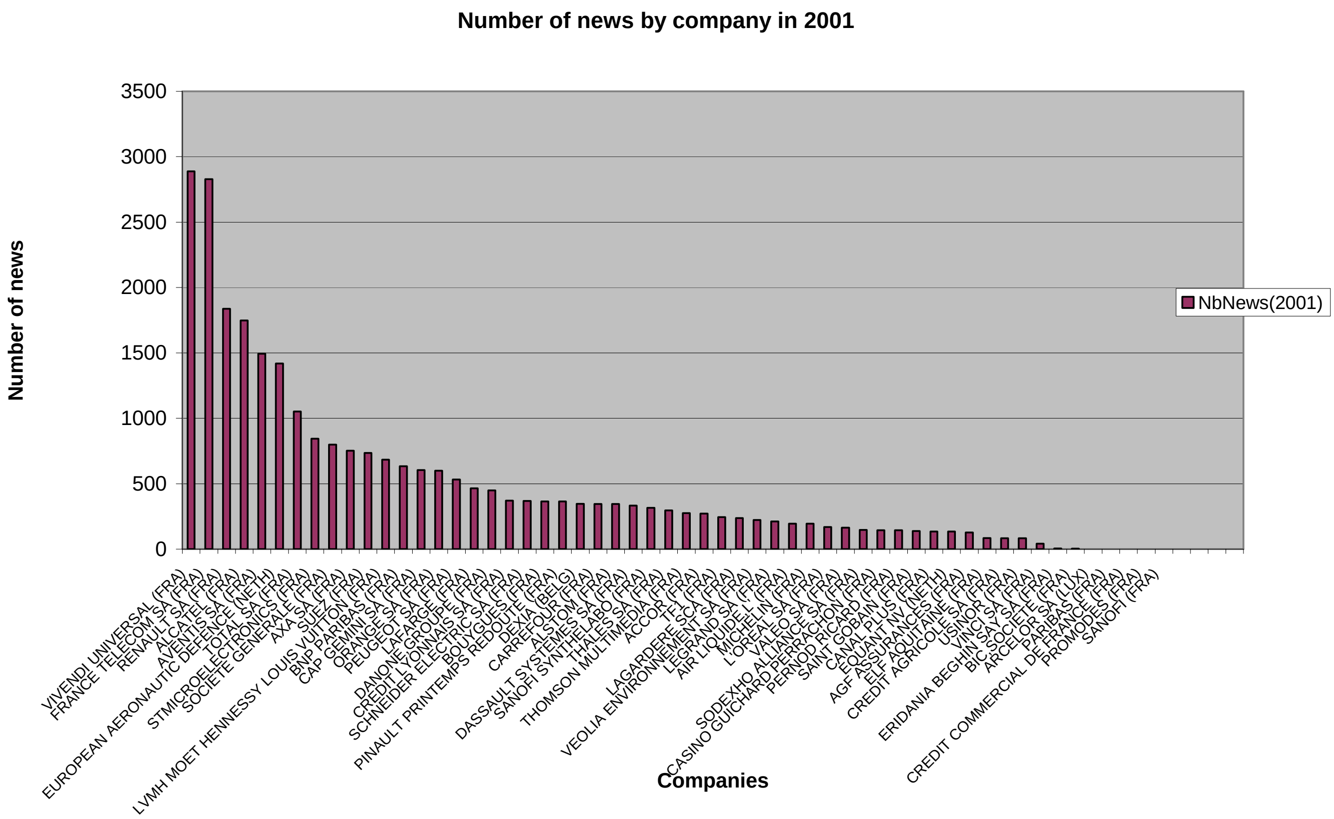


Figure 2

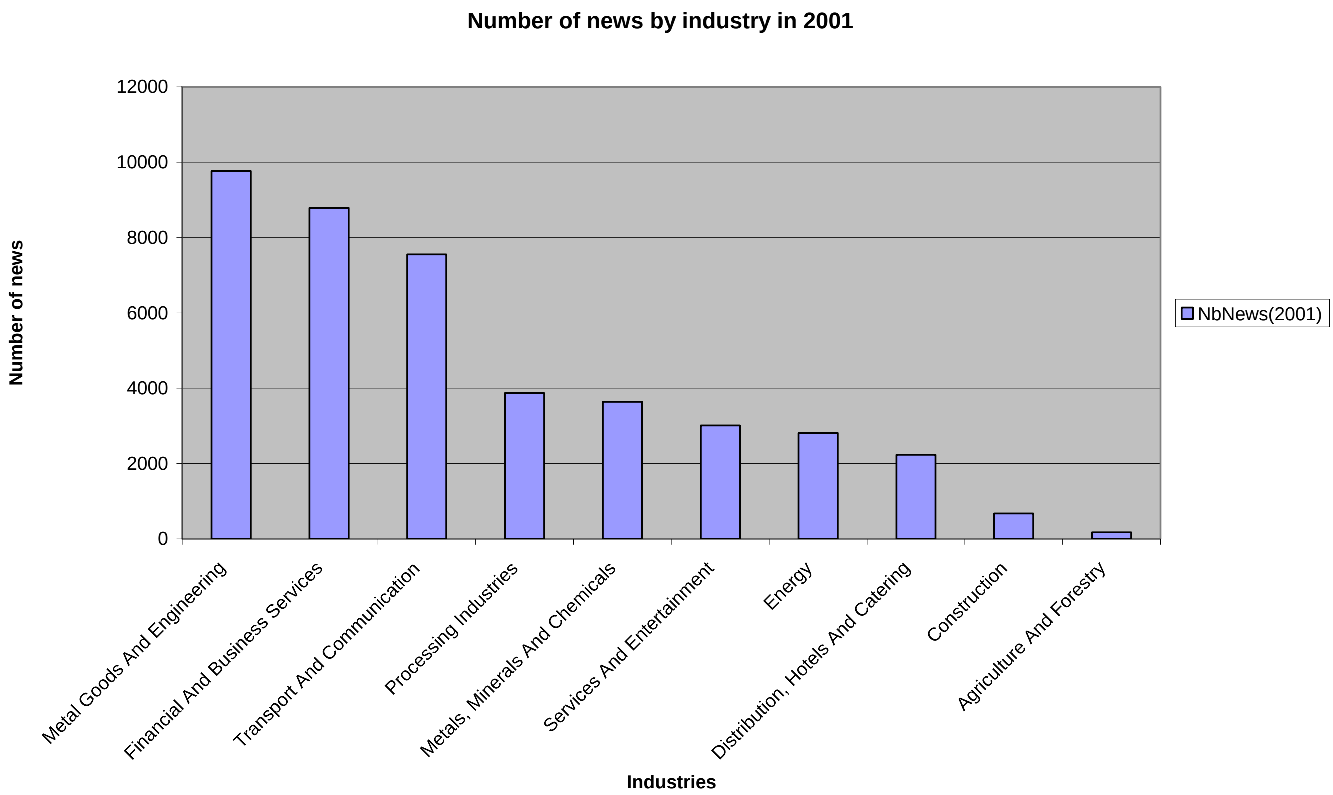
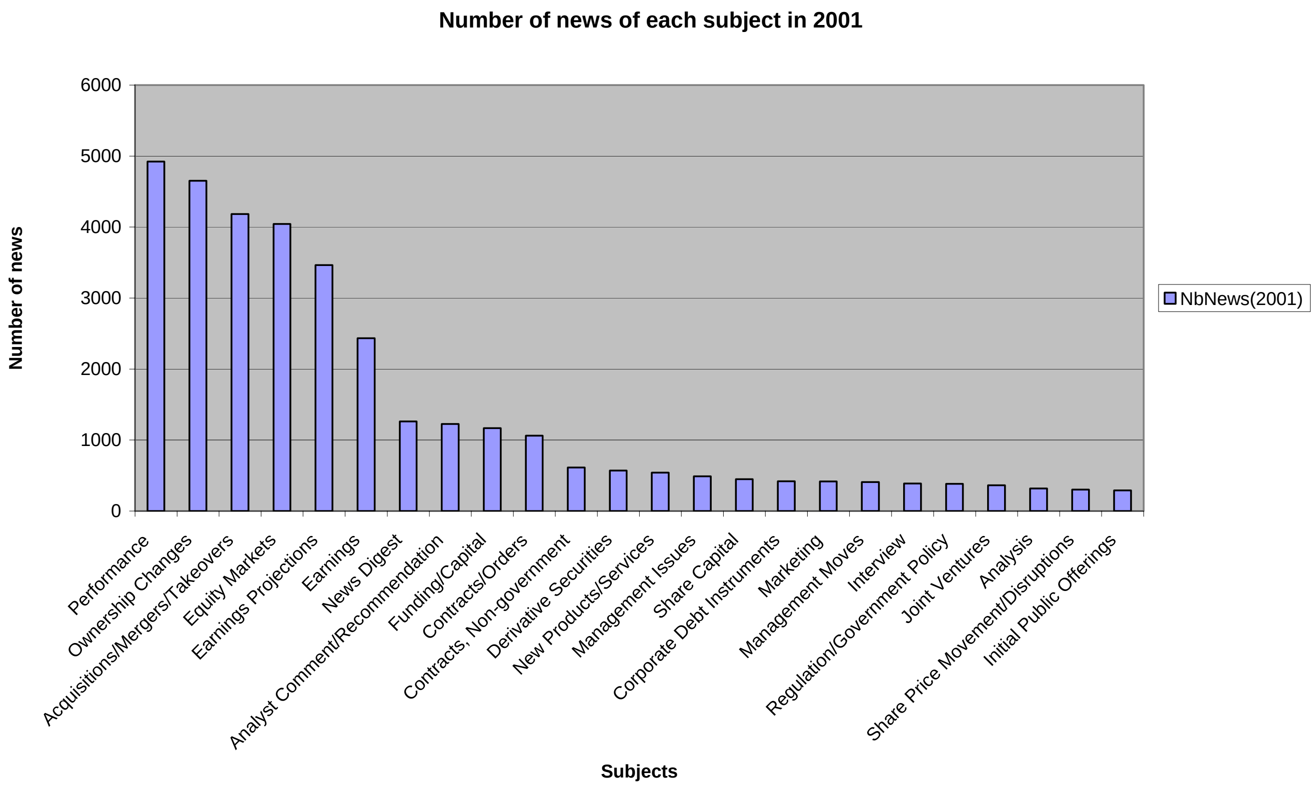


Figure 3



Number of news of each subject in 2001
6000
5000
4000
3000
2000
1000
0
Number of news
NbNews(2001)
Performance
Ownership Changes
Acquisitions/Mergers/Takeovers
Equity Markets
Earnings Projections
Earnings
News Digest
Analyst Comment/Recommendation
Funding/Capital
Contracts/Orders
Contracts, Non-government
Derivative Securities
New Products/Services
Management Issues
Share Capital
Corporate Debt Instruments
Marketing
Management Moves
Interview
Regulation/Government Policy
Joint Ventures
Analysis
Share Price Movement/Disruptions
Initial Public Offerings
Subjects

Table 1

Probit Regressions

Probit regression or each of the 48 securities, dependent variable $D_{i,d} =$ 1 if $P[S_{i,d} = 2] \geq 50\%$ (« high variance regime »), 0 otherwise (« low variance regime »). The conditional variance of market portfolio is estimated via a GARCH (1,1). 1270 observations.

		VU	*FT*	*RNLT*	*ALCATEL*	*AVENTIS*	*TOTAL*	*ST*
Probit	**C**	-2,72	-2,19	-0,11	-2,71	-0,82	-0,25	-0,02
	t-stat	*-23,51*	*-21,33*	*-1,50*	*-21,16*	*-10,83*	*-3,32*	*-0,40*
	Coeff-NBNEWS	0,07	0,03	0,06	0,07	0,07	0,09	0,02
	t-stat	*10,64*	*7,26*	*6,89*	*8,36*	*6,98*	*8,10*	*1,91*
	Coeff-VARCOND	3074,31	1981,19	518,80	2519,52	1311,79	267,38	-22,63
	t-stat	*13,44*	*10,24*	*2,91*	*11,59*	*7,25*	*1,51*	*-0,13*
	R^2	0,43	0,14	0,05	0,23	0,08	0,06	0,00

		lvmh	*BNP*	*capgem*	*peugeot*	*lafarge*	*Danone*	*schneid.*
Probit	**C**	-0,99	-0,82	-1,43	-0,98	-0,23	-0,15	-0,90
	t-stat	*-14,43*	*-10,63*	*-18,89*	*-13,81*	*-3,54*	*-2,29*	*-13,72*
	Coeff-NBNEWS	0,09	0,11	0,09	0,09	0,09	0,11	0,12
	t-stat	*7,95*	*9,59*	*7,16*	*5,42*	*4,40*	*5,80*	*5,56*
	Coeff-VARCOND	1406,10	1419,16	2695,09	1282,66	867,93	-530,10	824,60
	t-stat	*7,89*	*7,37*	*12,59*	*7,16*	*4,84*	*-2,95*	*4,63*
	R^2	0,10	0,11	0,20	0,07	0,04	0,04	0,05

		alstom	*dassault*	*sanofi*	*thales*	*accor*	*tf1*	*lagardere*
Probit	**C**	-2,15	-0,85	0,03	-0,17	-1,39	-0,34	-0,73
	t-stat	*-22,94*	*-13,45*	*0,44*	*-2,75*	*-19,20*	*-5,61*	*-10,94*
	Coeff-NBNEWS	0,10	0,04	0,04	0,09	0,10	0,09	0,15
	t-stat	*5,26*	*1,52*	*2,18*	*4,84*	*4,28*	*4,14*	*9,08*
	Coeff-VARCOND	2470,90	1346,46	877,42	108,81	1731,04	403,25	107,34
	t-stat	*12,36*	*7,53*	*4,57*	*0,63*	*9,32*	*2,33*	*0,58*
	R^2	0,20	0,05	0,02	0,02	0,09	0,02	0,09

		Valeo	*sodexho*	*casino*	*Pernod*	*St-Gobain*	*Equant*	*AGF*
Probit	**C**	-0,40	-1,08	-0,81	-0,60	-1,23	-1,06	-1,34
	t-stat	*-6,44*	*-16,33*	*-12,41*	*-9,61*	*-17,62*	*-15,45*	*-19,14*
	Coeff-NBNEWS	0,17	0,20	0,13	0,13	0,17	0,14	0,15
	t-stat	*5,60*	*5,54*	*6,13*	*4,32*	*6,28*	*7,03*	*4,19*
	Coeff-VARCOND	962,70	2047,03	562,39	1128,15	1684,49	2190,00	2667,56
	t-stat	*5,44*	*10,74*	*3,18*	*6,26*	*9,01*	*11,57*	*13,58*
	R^2	0,05	0,15	0,04	0,05	0,11	0,14	0,20

Follow-up of table 1

		EADS	Orange	Dexia	TMM	Veolia	Legrand	Elf
Probit	**C**	-1,58	-1,31	-2,51	-1,50	-1,48	-0,58	-1,28
	t-stat	*-16,07*	*-11,59*	*-21,00*	*-17,33*	*-17,02*	*-8,53*	*-17,45*
	Coeff-NBNEWS	0,03	0,19	0,21	0,08	0,05	0,06	0,05
	t-stat	*2,36*	*8,47*	*7,81*	*4,15*	*2,94*	*2,04*	*5,68*
	Coeff-VARCOND	1948,50	3354,75	3741,75	1035,17	2425,06	452,48	1423,08
	t-stat	*10,12*	*10,30*	*15,11*	*5,11*	*11,37*	*2,33*	*7,66*
	R^2	0,13	0,31	0,40	0,04	0,19	0,01	0,06

		SG	AXA	SUEZ	bouygues	ppr	carrefour	air liq.
Probit	**C**	-0,23	-2,25	-3,17	-0,65	-1,51	-0,65	-1,01
	t-stat	*-3,18*	*-17,93*	*-21,52*	*-10,02*	*-20,69*	*-9,86*	*-14,86*
	Coeff-NBNEWS	0,06	0,05	0,06	0,15	0,07	0,12	0,11
	t-stat	*6,17*	*4,37*	*4,48*	*8,96*	*4,93*	*8,28*	*5,09*
	Coeff-VARCOND	438,62	8070,05	6187,30	722,53	2348,06	231,97	691,83
	t-stat	*2,46*	*15,57*	*16,51*	*4,16*	*12,28*	*1,31*	*3,82*
	R^2	0,03	0,38	0,57	0,10	0,17	0,07	0,03

		michelin	l'oreal	arcelor	Vinci	Bic	Eridania
Probit	**C**	-1,91	-0,18	-0,49	-0,24	-0,96	-0,52
	t-stat	*-21,76*	*-2,82*	*-7,37*	*-3,96*	*-14,90*	*-3,29*
	Coeff-NBNEWS	0,17	0,10	0,32	0,02	0,65	0,31
	t-stat	*6,94*	*3,96*	*5,74*	*0,54*	*5,91*	*2,74*
	Coeff-VARCOND	1874,38	947,13	1872,76	-179,98	1367,16	2633,55
	t-stat	*9,57*	*5,06*	*9,23*	*-1,03*	*7,69*	*3,38*
	R^2	0,12	0,03	0,10	0,00	0,08	0,03

Table 2

OLS regressions

Probit regression or each of the 48 securities, dependent variable is the probability of being in the high-variance regime. The conditional variance of market portfolio is estimated via a garch (1,1). 1270 observations.

		VU	FT	RNLT	ALCATEL	AVENTIS	TOTAL	ST
OLS	**C**	-8,38	-5,04	-0,81	-4,77	-1,91	-1,85	-0,36
	t-stat	*-17,45*	*-20,96*	*-3,60*	*-27,62*	*-9,61*	*-5,26*	*-1,50*
	Coeff-NBNEWS	0,26	0,12	0,50	0,16	0,28	0,58	0,17
	t-stat	*11,67*	*11,40*	*11,13*	*13,52*	*8,85*	*7,59*	*3,57*
	Coeff-VARCOND	9163,65	6523,32	1595,97	4789,32	2813,62	1962,40	1471,59
	t-stat	*14,01*	*15,86*	*2,64*	*17,53*	*6,10*	*2,48*	*1,93*
	R^2	0,15	0,20	0,09	0,24	0,07	0,05	0,01

		lvmh	BNP	capgemini	peugeot	lafarge	danone	schneider
OLS	**C**	-2,48	-2,64	-3,20	-1,90	-1,22	-0,59	-1,85
	t-stat	*-13,19*	*-7,93*	*-18,27*	*-11,78*	*-4,63*	*-2,41*	*-13,49*
	Coeff-NBNEWS	0,48	0,33	0,36	0,25	0,49	0,80	0,51
	t-stat	*10,56*	*6,45*	*11,24*	*6,11*	*4,42*	*5,83*	*8,66*
	Coeff-VARCOND	4179,29	5288,32	6129,94	2947,24	5326,91	-989,27	1884,58
	t-stat	*8,55*	*5,59*	*12,70*	*7,31*	*5,83*	*-1,43*	*5,58*
	R^2	0,11	0,04	0,16	0,06	0,04	0,03	0,07

		alstom	dassault	sanofi-synth	thales	accor	tf1	lagardere
OLS	**C**	-6,98	-2,27	1,34	-1,26	-2,92	-2,04	-2,91
	t-stat	*-22,04*	*-13,90*	*5,56*	*-5,64*	*-18,05*	*-7,22*	*-12,37*
	Coeff-NBNEWS	0,62	0,15	0,35	0,75	0,32	0,90	1,05
	t-stat	*13,38*	*2,34*	*2,15*	*7,46*	*6,62*	*6,44*	*14,53*
	Coeff-VARCOND	8725,19	4499,12	-29,90	2413,11	3690,68	3062,14	1500,28
	t-stat	*17,66*	*9,47*	*-0,04*	*3,95*	*10,26*	*4,02*	*3,00*
	R^2	0,22	0,07	0,00	0,05	0,10	0,04	0,14

		Valeo	sodexho	casino	Pernod	St-Gobain	Equant	AGF
OLS	**C**	-1,56	-2,20	-1,41	-1,35	-3,29	-4,10	-5,78
	t-stat	*-8,73*	*-15,78*	*-11,97*	*-6,77*	*-15,57*	*-18,15*	*-18,06*
	Coeff-NBNEWS	1,10	0,74	0,40	0,80	0,84	0,45	0,58
	t-stat	*7,76*	*6,95*	*7,81*	*5,33*	*9,84*	*8,22*	*6,01*
	Coeff-VARCOND	3630,85	5142,26	898,42	3010,00	4468,77	12416,80	16481,30
	t-stat	*6,77*	*12,05*	*2,96*	*4,79*	*9,19*	*16,42*	*16,16*
	R^2	0,07	0,13	0,05	0,04	0,10	0,19	0,17

Follow-up of table 2

		EADS	Orange	Dexia	TMM	Veolia	Legrand	Elf
OLS	**C**	-3,73	-4,67	-5,11	-3,93	-3,38	-0,77	-3,27
	t-stat	*-14,58*	*-12,61*	*-24,92*	*-17,15*	*-13,12*	*-6,31*	*-18,06*
	Coeff-NBNEWS	0,08	0,68	0,43	0,27	0,19	0,28	0,19
	t-stat	*3,11*	*11,02*	*10,18*	*7,65*	*4,07*	*3,64*	*8,64*
	Coeff-VARCOND	5848,97	11857,80	8302,65	2167,73	6291,61	1373,90	4469,30
	t-stat	*12,87*	*10,29*	*20,51*	*6,05*	*9,21*	*3,92*	*11,42*
	R^2	0,16	0,20	0,30	0,07	0,10	0,03	0,11

		SG	AXA	SUEZ	bouygues	ppr	carrefour	air liquide
OLS	**C**	-0,30	-6,46	-7,96	-2,54	-2,64	-2,48	-2,29
	t-stat	*-1,21*	*-20,00*	*-15,71*	*-11,37*	*-23,50*	*-11,48*	*-15,66*
	Coeff-NBNEWS	0,15	0,29	0,22	1,16	0,23	0,71	0,59
	t-stat	*2,98*	*8,48*	*7,10*	*12,85*	*8,61*	*11,78*	*10,26*
	Coeff-VARCOND	2048,20	22703,50	16221,40	3385,63	4843,74	1423,00	1941,06
	t-stat	*2,80*	*19,86*	*13,85*	*6,32*	*15,72*	*2,95*	*5,69*
	R^2	0,01	0,24	0,13	0,13	0,19	0,10	0,09

		michelin	l'oreal	arcelor	Vinci	Bic	Eridania
OLS	**C**	-4,27	-0,25	-0,91	0,15	-1,96	-1,07
	t-stat	*-20,88*	*-1,13*	*-6,77*	*1,01*	*-11,77*	*-3,00*
	Coeff-NBNEWS	0,71	0,57	1,14	0,24	2,49	1,52
	t-stat	*11,96*	*4,01*	*7,67*	*1,98*	*6,79*	*2,41*
	Coeff-VARCOND	4170,61	2926,31	5081,91	-746,49	4040,00	8318,87
	t-stat	*11,66*	*3,99*	*10,35*	*-1,70*	*8,31*	*4,46*
	R^2	0,15	0,02	0,10	0,00	0,08	0,04

Table 3

Panel data analysis

Fixed and random effect approaches: The conditional variance of market portfolio and the conditional variance of the sector indexb are estimated via a garch (1,1). The panel is made of 40 securities with 1270 observations for each.

		Dependent variable: State (dummy)			*Dependent variable: Proba*		
		1	***2***	***3***	***1***	***2***	***3***
Fixed Effect	**C**	-	-	-	-	-	-
	t-stat	-	-	-	-	-	-
	Coeff-NBNEWS	0,02	0,02	0,01	0,02	0,02	0,01
	t-stat	*36,13*	*35,58*	*24,11*	*42,54*	*42,19*	*29,43*
	Coeff-VARCOND	-	432,74	114,01	-	396,63	102,54
	t-stat	-	*45,16*	*10,76*	-	*51,32*	*12,14*
	Coeff-VARCONDSECT	-	-	239,89	-	-	221,34
	t-stat	-	-	*61,52*	-	-	*71,21*
	R^2	0,11	0,15	0,21	0,14	0,18	0,25

		Dependent variable: State (dummy)			*Dependent variable: Proba*		
		1	***2***	***3***	***1***	***2***	***3***
Random Effect	**C**	0,32	0,20	0,16	0,34	0,23	0,19
	t-stat	*13,21*	*8,39*	*5,65*	*15,48*	*10,64*	*7,53*
	Coeff-NBNEWS	0,02	0,02	0,01	0,02	0,02	0,01
	t-stat	*36,03*	*35,49*	*24,03*	*42,44*	*42,09*	*29,36*
	Coeff-VARCOND	-	432,78	115,09	-	396,66	103,30
	t-stat	-	*45,16*	*10,86*	-	*51,32*	*12,23*
	Coeff-VARCONDSECT	-	-	239,11	-	-	220,79
	t-stat	-	-	*61,38*	-	-	*71,09*
	R^2	0,01	0,04	0,06	0,01	0,05	0,08

APPENDIX

Proportion data regression

The dependent variable is the proportion (P_i) of the ni individuals. The regression analysis of P_i, as shown in Greene (2000, p. 835), raises a concern of heteroscedasticity. The observed P_i is an estimate of the population quantity, $\pi_i = F(\beta X_i)$. If we treat this problem as sampling from Bernoulli population, then we have:

$$P_i = F(\beta X_i) + \varepsilon_i = \pi_i + \varepsilon_i \qquad \text{(A2.1)}$$

where:

$$E[\varepsilon_i] = 0\,,\ Var[\varepsilon_i] = \frac{\pi_i(1-\pi_i)}{n_i} \qquad \text{(A2.2)}$$

This heteroscedastic regression format suggests that the parameters could be estimated by a nonlinear weighted least squares regression. But the author proposes a simpler way to proceed. Since the function $F(\beta X_i)$ is strictly monotonic, it has an inverse.

$$F^{-1}(P_i) = F^{-1}(\pi_i + \varepsilon_i) \approx \beta X_i + \frac{\varepsilon}{\int_i} \qquad \text{(A2.3)}$$

This equation produces a heteroscedastic linear regression:

$$F^{-1}(P_i) = Z_i = \beta X_i + u_i \qquad \text{(A2.4)}$$

where:

$$E[u_i] = 0\,,\ Var[u_i] = \frac{F_i(1-F_i)}{n_i \int_i^2} \qquad \text{(A2.5)}$$

The inverse function for the logistic model is easy to obtain. If

$$\pi_i = \frac{\exp(\beta X_i)}{1+\exp(\beta X_i)} \qquad \text{(A2.6)}$$

then:

$$Ln\left(\frac{\pi_i}{1-\pi_i}\right) = \beta X_i \qquad \text{(A2.7)}$$

Weighted least squares regression produced the minimum χ^2 estimator of β. Since the weights are function of the unknown parameters, a two step procedure is called for. Simple least squares at the first step produces a consistent but inefficient estimate. Then the weights for the logit model based on the first step estimates are then:

$$W_i = n_i \Lambda_i (1 - \Lambda_i) \text{ with } \Lambda_i = \frac{\exp(\beta X_i)}{1 + \exp(\beta Xi)} \qquad \text{(A2.8)}$$

and can be used for weighted least squares in the second step procedure.

References

Beaver, William H., 1968, « The information content of annual earnings announcements », Empirical Research in Accounting 6: 67-92.

Berry, T.D., and K. M. Howe, 1993, « Public information arrival », *Journal of Finance*, 49, 1331–1346.

Campbell, J. Y., M. Lettau, B. Malkiel and Y. Xu, 2001, « Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk », *Journal of Finance,* 56:1-43, February 2001. Winner of Smith Breeden Prize, 2001.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001, « Evidence on the Speed of Convergence to Market Efficiency », forthcoming: *Journal of Financial Economics*.

Clark, P. K., 1973, « A subordinated stochastic process model with finite variance for speculative prices », *Econometrica*, 41, 135-155.

Easley, D., and M. O'Hara, 2004, « Information and the Cost of Capital », *The Journal of Finance*, 59(4), 1553-1583.

Ederington, L.H., and J. H. Lee, 1993,. How markets process information: News releases and volatility, Journal of Finance 48, 1161–1191.

Fama, E. F., 1970, « Efficient Capital Markets : a review of theory and empirical work », *Journal of Finance*, 25, 383-417.

Fama, E., Fisher, L., Jensen, M., Roll, R., 1969, « The adjustment of stock prices to new information », *International Economic Review,* 10, 1-21.

Goyal, A., and P. Santa-Clara, 2003, « Idiosyncratic Risk Matters! », *Journal of Finance*, 58, 975-1007.

Greene, W., 2002, « Econometric Analysis », Fourth edition, *Prentice Hall*.

Hamilton, J., 1989, « A New Approach to the Economic Analysis of Nonstationary Time Series and The Business Cycle », *Econometrica*, 57, 357-84.

Hamilton, J., 1994, « Time series analysis », *Princeton University Press*.

Kalev, P. S., W.-M. Liu, P. K. Pham et E. Jarnecic, 2004, « Public Information Arrival and Volatility of Intraday Stock Returns », *Journal of banking and Finance*, 28(6), 1447-1467.

Krolzig, H.M., 1997, « Markov-Switching Vector Autoregressions », *University of Oxford*, UK Lecture Notes in Economics and Mathematical Systems, Vol. 454, Springer, XIV.

Mitchell, M. L. et J. H. Mulherin, 1994, « The Impact of Public Information on the Stock Market », *Journal of Finance*, 49, 923-950.

Roll, R., 1984, « Orange Juice and weather », *The American Economic Review*, 74(5), pp. 861-880.

Roll, R., 1987, « R-Squared », *Journal of Finance*, 43, 541-566.

Ross, S. A., 1989, « Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy », *Journal of Finance*, 44, 1-17.