Abstract

The first purpose of this paper is to determine if the volatility of stock prices of social responsible companies is different compared to volatility of stock prices of the companies which are not social responsible. We used for the empirical study High Frequency Data for 64 stocks of companies from both categories, for 20 trading days in June 2013. The results show that the volatility of stock prices is lower for social responsible companies. The second purpose is to determine the parameters estimates for the HEAVY Model used to forecast the short term volatility of Webmd Health Corporation stock prices.

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1. Introduction

The interest in developing new methods to analyze, estimate and forecast the risk of stock markets has increased since High Frequency Data appeared. High Frequency Data in finance involve time series or prices and quantities associated to these prices. With this new type of data, statisticians are more and more challenged to handle a huge number of observations with specific characteristics, different from usual types of finance data.

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According to Takahashi and Shoji (2011) the risk of a stock market is measured by the volatility of its stock price indexed in time series and this can be calculated more accurate using High Frequency Data. Also, the utilization of High Frequency Data improves the quality of short term forecasting volatility.

The aim of this paper is to conduct an empirical analysis by using High Frequency Data in order to see if the volatility of stock prices of the most 32 social responsible companies is different from the volatility of stock prices of the less 32 social responsible companies, to see if corporate social responsibility can make any difference when measuring and forecasting the volatility.

Corporate Social Responsibility (CSR) was defined by Choi et al. (2010) as actions that appear to further some social good, beyond the interests of the firm and that which is required by law.

Development of CSR is related to the development of Socially Responsible Investment (SRI) which is a new trend of socially responsible activity, meaning that more investors are willing to trade stocks of social responsible companies and are willing to form SRI funds and even SRI indexes. During the last decade SRI has been growing over the world and has become a multibillion dollar market (Zekiene et al. 2011), meaning that bigger and bigger amounts are involved.

Many studies have tried to demonstrate the dependence between the social performance of companies and their financial performance, but we’re not aware of any study made in order to demonstrate if volatility of stock prices is influenced by the corporate social responsibility, particularly using High Frequency Data.

The organization of this paper is as it follows. The second section presents the data used for the empirical study. The third section treats the theoretical side of volatility: how to measure and how to model it. The fourth part presents the results of the empirical effectuated study. The final section presents conclusions and future directions for work.

2. Data

The necessary High Frequency Data were daily retrieved through QuantShare software and analyzed using statistical software R cran, “highfrequency” package. For each 1-minute interval, QuantShare retrieved the number of transactions and 4 types of prices: Open, High, Low and Close. In the current analysis only Close Price will be used, being the latest value of a stock price for 1-minute interval.

The total dimension of the sample is 64 stocks which can be seen in Table 1. The sample period is from the 1st of June 2013 until the 30th of June 2013, giving a total of 20 trading days on the major stock exchanges of the world. The data are only for the daily interval of time opening at 9:00 and closing at 16:00.

32 companies in the sample are among the first 35 responsible companies in the list published by the Corporate Responsibility Magazine in 2013: “CR’s 100 Best Corporate Citizens 2013”. This top list was realized by giving points to each company for many domains (environment, human rights, philanthropy, corporate governance, etc.). As fewer points a company had, as high it was its place in the list.

The other 32 companies in the sample are for the companies which were in “The 2012 Black List” published by the same Corporate Responsibility Magazine in 2012. This list had 35 companies, but data were available only for 32 companies. This “Black List” included companies who failed to provide information about corporate behaviour, who failed to provide the minimal transparency about their social corporate performance, even if in reality they’re committed to environmental sustainability.

3. Methodology

The methodological section of the paper aims to present some specific methods found by specialists in order to measure the volatility of stock prices and to show how parameter estimates of a model based on High Frequency Data can be determined.
3.1. Measuring Volatility – Daily Returns

Volatility of a stock price cannot be directly observable, but the most popular way to measure the daily volatility is to use the daily squared returns. Andersen and Bollerslev (1998) showed that the daily squared return is an unbiased estimator of the true volatility. Lu and Lin (2010) wrote the following equation to compute volatility:

\[ \sigma_t^2 = \int \sigma_{t+r}^2 \, dr \]

Dettling and Buhlmann (2004) are more specific. They’re considering the series of high frequency returns with \( m \) observations per day as being defined by the logarithmic difference of the closing prices:

\[ r_{(m),t} = \ln(P_{(m),t}) - \ln(P_{(m),t-1}) = t = \frac{1}{m}, \frac{2}{m}, \ldots \]

where \( r \) – daily returns, \( P \) – Closing Price for 1-minute interval.

For our empirical approach we use the following estimator for the daily volatility given by Zumbach et al. (2002):

\[ \sigma^2 = \frac{1}{n} \sum r(j)^2 , \]

where the sum covers one day of data, \( n \) is the number of ticks during the day, and the return \( r \) is the same as the one determined previously as a difference between the logarithmic prices.

We calculated returns based on the prices for 1-minute interval from 9.30 to 16:00. As there are 20 full trading days during the sample period, the maximum of observations available for one stock is a total of 390. But there are some stocks which are not so frequently traded (not at every minute), so the number of transactions would be lower. In this case, the return is based on the prices at the following available minute.

3.2. Modeling Volatility – HEAVY Model

Choosing the best model to describe the past and to predict the future in the same time is not an easy task. From far, the most popular class of econometric models for describing a series with time-varying conditional variance is the Autoregressive Conditional Heteroscedasticity (ARCH) class of models. But then, in the latest few years, General Autoregressive Conditional Heteroscedasticity (GARCH) models have found wide use in modeling distribution of assets returns (Oral, 2012).

However, analyzing daily returns using High Frequency Data can improve not only the volatility measurement processes, but the volatility forecast processes as well (Lu et al. 2010). This is the reason which determined Neil and Kevin Sheppard (2010) to develop the HEAVY (High-frEQuency-bAsed VolatilitY) Model, a model that is focusing to predict volatility, rather than measuring it, like previous models did.

Unlike GARCH models, HEAVY models bring two sources of information:

- daily financial returns: \( r_1, r_2, \ldots, r_T \)
- a corresponding sequence of daily realized measures: \( RM_1, RM_2, \ldots, RM_T \)

The model is given by 2 equations:

- the first one models the close-to-close conditional variance (Boudt et al.):
  \[ \text{Var}(r_t|T=1) = h_t = \omega + \alpha RM_{t-1} + \beta h_{t-1}, \text{ where } \omega, \alpha \geq 0 \text{ and } \beta \in [0,1] \]

- the second one models the conditional expectation of the open-to-close variation
  \[ E(RM_t|T=1) = \theta_t = \omega_r + \alpha_r RM_{t-1} + \beta_r \theta_{t-1} \]
where $\theta_R, \alpha_R, \beta_R \geq 0$ and $\alpha_R + \beta_R \in [0,1]$

Each parameter of the model ($\omega, \omega_R, \alpha, \alpha_R, \beta, \beta_R$) can be obtained using Quasi-maximum likelihood. In order to determine each daily realized measure, $RM_t$, a class estimator that is somehow robust to the noise of High Frequency Data has been suggested by Barndorff et al. [11] and will be used is the realized kernel.

4. Empirical results

In order to see if the volatility of stock prices of the most responsible companies is different from the volatility of stock prices of the “Black List” companies, we’re calculating the monthly average of daily squared returns:

$$M_m = \sum_{m=1}^{20} \frac{r_1^2 + \cdots + r_m^2}{m}$$

with $m$ – number of days in June and $t$ – 1-minute interval time between 9:30 and 16:00.

These monthly averages return ($M$) for each company can be seen in the Table 1. In order to make the results more visual, the average was multiplied by 1,000,000.

To have a better picture about the differences between the 2 categories of companies, we can determine the total of monthly average of daily squared returns ($MR_c$) for all the companies:

$$MR_c = \sum_{c=1}^{32} M_1 + \cdots + M_c$$

with $s1$ – category of social responsible companies and $s2$ – category of the companies in the “black list”.

| Rank | Company Code | Monthly Average Returns (x1,000,000) | Rank | Company Code | Monthly Average Returns (x1,000,000) |
|------|--------------|---------------------------------------|------|--------------|---------------------------------------|
| 23   | UPS          | 0.27209                               | 9    | AXS          | 0.45334                               |
| 31   | MSI          | 0.42144                               | 18   | HCC          | 0.55659                               |
| 33   | MMM          | 0.43224                               | 6    | ARCC         | 0.60815                               |
| 11   | IBM          | 0.44106                               | 4    | AFG          | 0.66076                               |
| 32   | GIS          | 0.48722                               | 34   | TMK          | 0.68088                               |
| 16   | JNJ          | 0.51524                               | 31   | RNR          | 0.72343                               |
| 24   | PX           | 0.52006                               | 16   | FRC          | 0.78005                               |
| 25   | DUK          | 0.54525                               | 23   | LINTA        | 0.86262                               |
| 18   | MO           | 0.54694                               | 14   | ENH          | 0.91212                               |
| 15   | DD           | 0.54964                               | 25   | LO           | 0.94120                               |
| 17   | KMB          | 0.55704                               | 7    | ARW          | 0.97647                               |
| 7    | HAS          | 0.55863                               | 15   | FNFG         | 1.27995                               |
| 14   | KO           | 0.57803                               | 27   | NFG          | 1.32118                               |
| 2    | MAT          | 0.59935                               | 12   | DWA          | 1.42201                               |
| 1    | T            | 0.59950                               | 32   | SLGN         | 1.44346                               |
Only 3 social responsible companies had the monthly average of daily squared returns higher than 1. In the second category (“Black List” companies) 21 companies had this monthly average higher than 1, and 7 companies had values even higher than 2.

The total of monthly average of daily squared returns (MR) for the social responsible companies is 

\[ MR_s1 = 21.93913 \]

and for the companies in the “Black List” is 

\[ MR_s2 = 51.85234 \]

Overall, it seems that the volatility of stock prices of the companies in the “Black List” is higher than the volatility of the stock prices of the social responsible companies. That means that the risk is higher when investing in “Black List” companies stocks, but also the chances to have bigger returns/looses are higher.

The biggest monthly average of daily squared return, 4.44342, is for WBMD – WebMd Health Corporation. In spite of its name, this company has the 35th place in the “Black List”.

Table 2. Daily Squared Returns for WBMD

| Day  | Daily Squared Returns (x1,000,000) |
|------|---------------------------------|
| Day1 | 11.50263                        |
| Day2 | 2.175575                        |
| Day3 | 6.95596                         |
| Day4 | 4.032855                        |
| Day5 | 4.648466                        |
| Day6 | 2.652002                        |
| Day7 | 2.838763                        |
| Day8 | 3.992602                        |
| Day9 | 3.197966                        |
| Day10| 1.747288                        |

We have to find out what determined this high level of volatility. Table 2 shows that the first trading day (the 3rd of June 2013) and the 20th trading day (the 28th of June 2013) have the highest level of squared returns.

A better image about what happened during these 2 days can be obtained looking deeply into the High Frequency Observations. On the 3rd of June, the WBMD stock price increased from 28.98 at 9.30 to 30.14 at 11:46, and then
linearly until the end of the trading day. Future investigations could explain this increasing (maybe the spread of some news on the market), but this is not the purpose of our study at this moment.

A high volatility was measured on the 28th of June, as well, when the stock price increased from 27.81 at 9:30 to 29.6 at 10:42 and then fluctuated until the end of the trading day.

After measuring the volatility during the month of June, we can determine the estimates of parameters and the volatility using HEAVY model only for WBMD stock prices.

In matrix notations, the HEAVY model can be written as:

\[
\begin{pmatrix}
    h_t \\
    \theta_t
\end{pmatrix} = \begin{pmatrix}
    \omega \\
    \omega_R
\end{pmatrix} + \begin{pmatrix}
    \alpha \\ \\
    \alpha_R
\end{pmatrix} \begin{pmatrix}
    r^2_{t-1} \\
    RM_{t-1}
\end{pmatrix} + \begin{pmatrix}
    \beta \\
    \beta_R
\end{pmatrix} \begin{pmatrix}
    h_{t-1} \\
    \theta_{t-1}
\end{pmatrix}
\]

, and it will have the following parameter estimates:

\[
\begin{align*}
\omega &= 0.007 \\
\omega_R &= 0.032 \\
\alpha &= 0.455 \\
\alpha_R &= 0.410 \\
\beta &= 0.763 \\
\beta_R &= 0.569
\end{align*}
\]

These estimates are close to Shephard’s (2010) expectations meaning that, in applied work, β estimate should be around 0.6-0.7 and ω should be very small. Anyway, this type of model is more accurate than GARCH type of models when predicting short term values. To predict the long term, Shephard recommend GARCH models.

A more complex model with more stock prices is in it will be built in the following papers. Future developments will include also outputting standard errors, as soon as the utilized statistical software will have finished the implementation of the HEAVY model.

5. Concluding Remarks

This paper aimed to investigate if the volatility of stock prices of social responsible companies is different from the volatility of stock prices of companies who didn’t adopted, or didn’t made official reports about their social responsibility politics. Contrarily to our expectations, the 32 stock prices of companies in the “Black List” have a higher volatility than the 32 stock prices of social responsible companies, meaning that the risk and the chances to have bigger returns/looses are higher when investing in these “Black List” companies stocks. The company with the highest volatility of stock prices is WBMD.

Beside the measurement of volatility, using High Frequency Data improved the process of forecast the volatility. This was possible by building a model that has 2 sources of information, not just one source as GARCH models have. We used the HEAVY Model and High Frequency Data for WBMD stock prices and we obtained the estimates parameters of the model accordingly to Shephard’s expectations for this kind of data and this type of model.

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