University of Ioannina

Department of Economics

MSc in Economic Analysis

"Price returns and trading volume changes in stock market:An empirical analysis with quantile regressions"

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January 14, 2020

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Abstract

0.1 Abstract

The present study examines the relationship between closing price returns and volume changes in four firms which process and package meat.It is about a sample of daily data which concern the period of November 2009 until October 2019. The method that is used in order to analyze the data is quantile regression. The results suggest that there is relationship between these two variables. In particular, according to results, there is a stable but not extreme influence and correlation between closing price returns and volume trade. At the same time, there is a co-movement at the low and high quantiles of the dependent variable.

Keywords: closing price returns,volume trade,processing and packaging firms,quantile regression

1 Introduction

1.1 The impact of the stock market in the economy

The stock market refers to the collection of markets and exchanges where regular activities of buying, selling, and issuance of shares of companies take place.Such financial activities are conducted through institutionalized formal exchanges or over-the-counter (OTC) marketplaces which operate under a defined set of regulations.There can be multiple stock trading venues in a country or a region which allow transactions in stocks and other forms of securities.

Movements in the stock market can have a profound economic impact on the economy and individual consumers. A collapse in share prices has the potential to cause widespread economic disruption.A characteristic example was the stock market crash of 1929.This crash had a profound impact on the economy and thus on human lives the decade of 1930.Daily movements in the stock market can also have less impact on the economy.However, the stock market is not the real economy.

As far as the firms(Tyson, Hormel Foods, Sysco Corporation, ConAgra Brands) concerned belong in the top ten meat packaging firms in U.S.A. and hold an important position in the stock market and the economy.Tyson is the world's second largest processor and marketer of chicken, beef, and pork after JBS S.A. and annually exports the largest percentage of beef out of the United States. In 2001, Tyson Foods acquired IBP, Inc., the largest beef packer and number two pork processors in the

United States, for US 3.2 billion dollars in cash and stock.In 2007 acquired Swift(the third largest packer) and in 2008 bought Smithfield(the fifth largest packer).

In 2011, Hormel Foods announced a two-for-one stock split. In 2013, Hormel Foods purchased Skippy—the best-selling brand of peanut butter in China and the second-best-selling brand in the world— from Unilever for 700 million dollars; the sale included Skippy's American and Chinese factories.In May 2015, Hormel revealed it would acquire meat processing firm Applegate Farms for around 775 million dollars, expanding its range of meat products.

On July 20, 2009, Fortune magazine ranked Sysco No. 204 in the annual Fortune 500 companies in the world based on sales volume. On May 3, 2010, Fortune ranked Sysco as the 7th largest Fortune 500 Company in Texas and 55th largest in the U.S. by total revenue.The company ranked No. 54 in the 2018 Fortune 500 list of the largest United States corporations by total revenue.In December 2013, Sysco announced an 8.2 billion dollars planned acquisition of its largest food distribution rival, US Foods.

On November 27, 2012, Conagra officials announced the company was purchasing Ralcorp, pending Ralcorp shareholder approval, for approximately 4.95 billion dollars. Stockholders of Ralcorp Holdings Inc. would receive 90 dollars per share. The deal completed in January 2013 and made ConAgra the largest private-label packaged food business in the United States.All these transactions reveal that firms hold an important position in the economy and that stock market exert influence ,also, in the economy.

2 Literature review

2.1 Theoretical Background

It is well known that the relationship between closing price and volume trade was an important topic for researchers and economists for many years. In other words, a lot of empirical works have been focused in order to find the connection between these two variables. This topic concerns not only the economists but also policy-makers. This happens because closing price and volume changes give them a lot of information about the structure of financial markets, the degree of stability of prices and the level of speculation activity. All these clues indicate the way that investors react when they have an information about financial markets.

As we have already mentioned there is bibliography and surveys which describe the relationship between closing price and volume changes.To be more specific, L.Blume, D.Easley and M O'Hara(1994) (16) developed a new theoretical stock market model that involves traders in which aggregate supply is fixed and traders receive signals with differing quality. In this way, they show that price returns and volume changes association is convex. L.Blume, D.Easley and M. O'Hara(1994) (16) were the first researchers that analyzed the presence of non-linearity. Until 1994, empirical works relied on simple correlation or on linear regression analysis. Furthermore, M.Karpoff(1987) (12) argued that volume is positively related to the magnitude of the price change and, in equity markets, to the price change.

After that in 2009 Ning and Wirjanto (3) examine East-Asian equity markets. The empirical results indicated that there is significant and asymmetric return–volume dependence at extremes for these markets. To be more particular, extremely high returns tend to be associated with extremely large trading volumes. On the other hand, extremely low returns tend not to be related to either large or small volumes. Chen(2012) (2) from his side investigated whether the empirical linkages between stock returns and trading volume differ over the fluctuations of stock markets. He found a positive (negative) contemporaneous correlation in “bear” (“bull”) markets that he analyzed. In 2018 Yi-Chiuan Wang and Yi Hao Lai (21) examined the return–volume dependence structure across six major international stock markets using a dependence-switching copula model. Their findings indicate that extreme high volumes tend to synchronize with both extreme high and extreme low returns but low volumes have no significant relationship with either extreme low or extreme high returns.

The objective of the present work is to investigate the linkage between price returns-volume changes associations in financial markets.This is pursued using daily data from 2009 to 2019 and quantile regressions.Our analysis takes into consideration the earlier theoretical results.It focuses on a market which influences not only the economy of U.S.A. but also the international economy.This happens because the firms that are used in our analysis, not only stock the domestic market but also belong to the largest exporters of packaging meat in countries like Mexico, Brazil, Canada, Colombia and Argentina.

3 Data and methodology

3.1 Data collection

The data that are used in our analysis collected from the 1st of November 2009 until the 31st of October 2019. So, it is about a sample of 10 years. Data are obtained from one data frame and more specifically, yahoo finance which has international market data.Our data are daily and concern open, close, high and low prices and volume of four firms (Tyson Foods, Hormel Foods Corporation, Sysco Corporation and Conagra Brands) which belong in the top 10 firms of pork and beef packers in the United States.The volume of each firm shows how many transactions have been made in one day (trading). In the same time, prices and volume of each firm are logarithms.In quantile regression analysis we take the differences of logarithms.

3.2 Daily plots

This part presents the evolution that the logarithm close price and volume have between the period of 1st of November 2009 until the 31st of October 2019. As shown at figure 3.1 at 3.2 at 3.3 and at 3.4 there is a spectacular increase of the daily close price for firms the recent periods.The only firm that is an exception to this is CAG which is decreased in recent periods and more particularly after 2017.

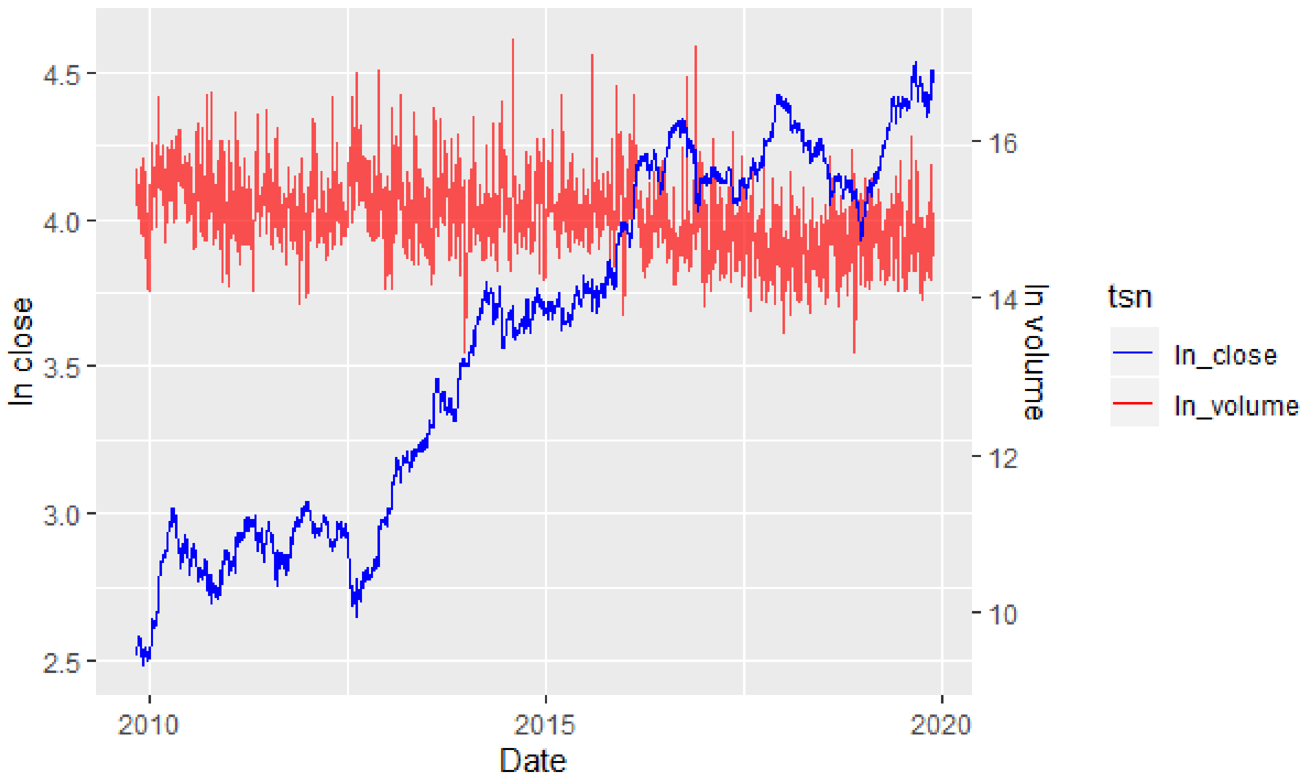

Figure 3.1: tsn logarithm of price and volume

As far as daily closing price concerned, the downward trends of the past have been replaced with upward trends in the recent periods.So daily closing price generally exhibit downward trends in earlier periods and upward trends in the recent ones. The closing price is bigger for TSN and SYY as 3.1 at 3.2 at 3.3 and at 3.4 show and lower for CAG and HRL.

Then, in figures 3.1, 3.2, 3.3 and 3.4 we observe how the volume of trade moves over the years including the fluctuations of transactions. The volume time series show considerable variability without any visible tendency for an increase or a decrease.An exception to this was SYY(Sysco Corporation) in 2013 where it is noticed an extreme increase due to the fact that Sysco announced an 8.2 billion dollars planned acquisition of its next-largest food distribution rival, US Foods.

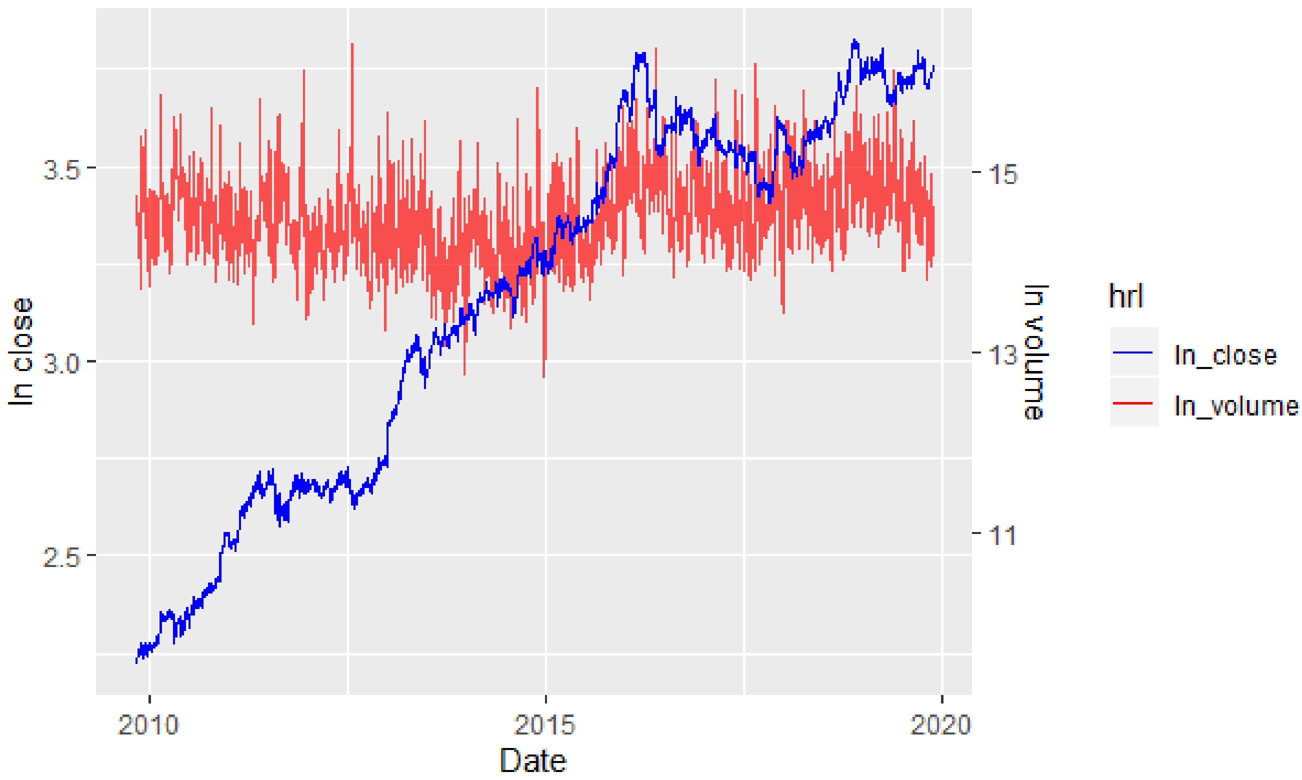

Figure 3.2: hrl logarithm of price and volume

3.3 Methodology:what is quantile regression

Quantile regression methods have been widely used in economics to study different economic indicators and variables.This happens because quantile regression is capable of providing a more complete statistical analysis of the stochastic relationships among random variables.Quantile regression is a statistical technique intended to estimate and conduct inference about, conditional quantile functions.Just as classical linear regression methods based on minimizing sums of squared residuals enable one to estimate models for conditional mean functions, so does the method quantile regression estimating models for the conditional median function, and the full range of other conditional quantile functions.In other words, the method of fewest squares estimates the conditional means of the response variable given certain values of the predictor variables while quantile regression aims at estimating either the conditional median or other quantiles of the response variable.So, quantile regres-

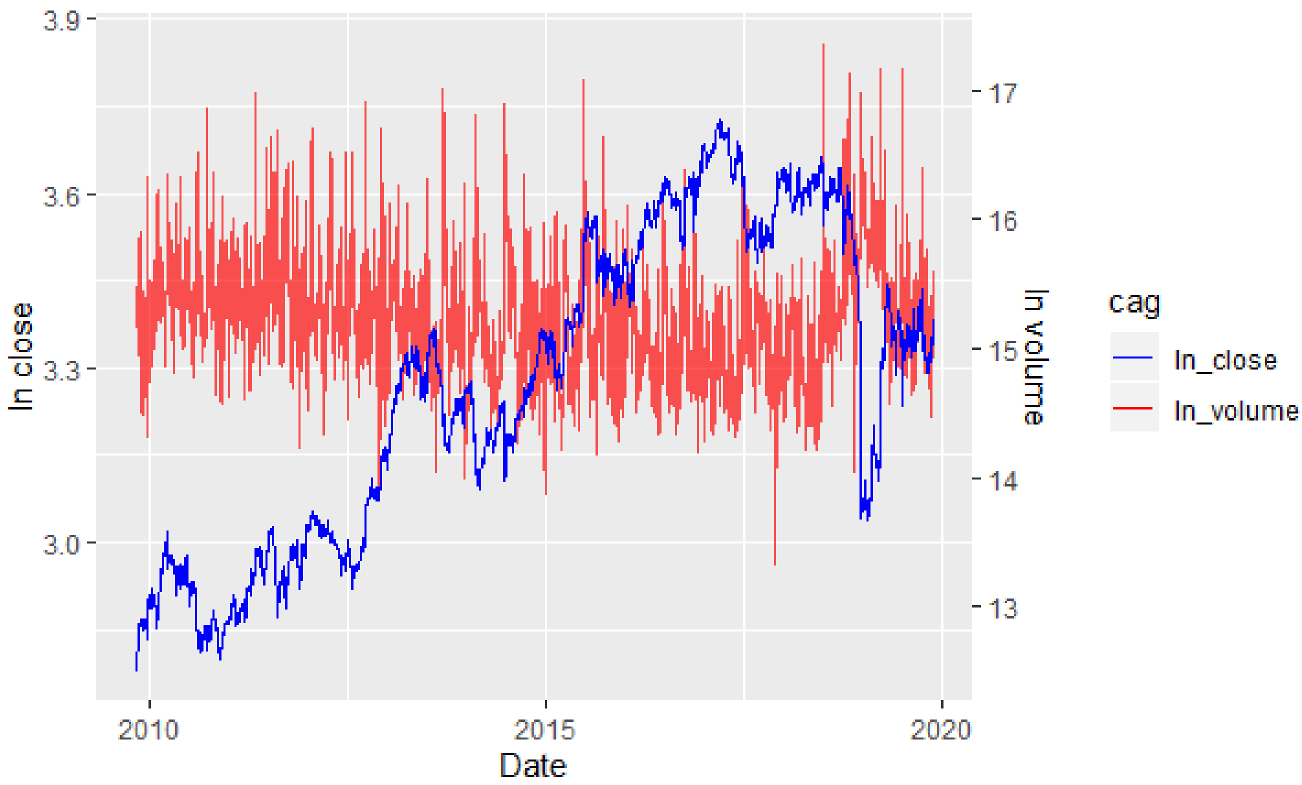

Figure 3.3: cag logarithm of price and volume

sion is the extension of linear regression, and it is used when the conditions of linear regression are not applicable.

3.4 Quantile regression:History

The idea of estimating a median regression slope was proposed in 1760 by Ruđer Josip Bošković.He was interested in something that did not have any relationship with economy:the ellipticity of the earth, building on Isaac Newton's suggestion that its rotation could cause it to bulge at the equator with a corresponding flattening at the poles.He produced the first geometric procedure for determining the equator of a rotating planet from three observations of a surface feature. More importantly for quantile regression, he was able to develop the first evidence of the least absolute criterion and preceded the least squares introduced by Legendre in 1805 by fifty years.

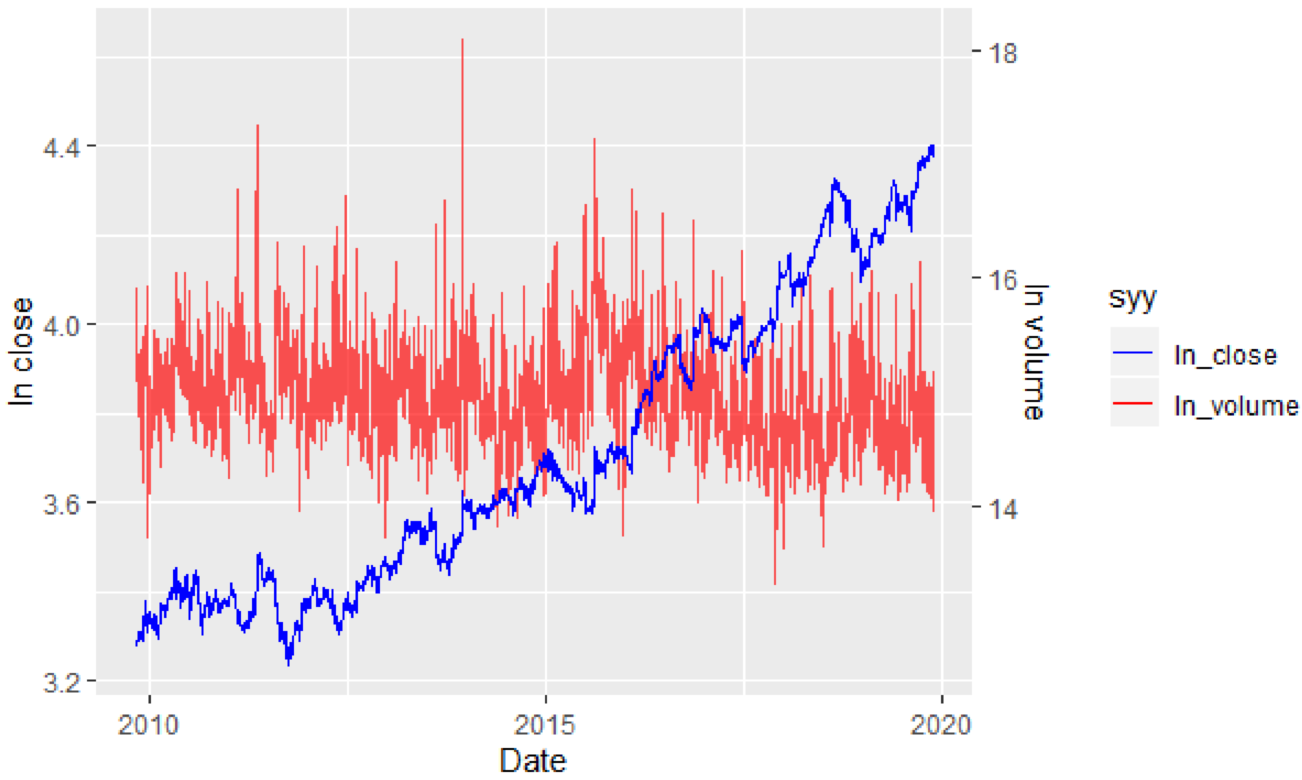

Figure 3.4: syy logarithm of price and volume

Other thinkers began building upon Bošković's idea such as Pierre-Simon Laplace, who developed the so-called "methode de situation." This led to Francis Edgeworth's plural median - a geometric approach to median regression - and is recognized as the precursor of the simplex method. The works of Bošković, Laplace, and Edgeworth were recognized as a prelude to Roger Koenker's contributions to quantile regression.

In the past, a lot of researchers offered theirs analysis on the subject of quantile regression. Quantile Regression Model (QRM) according to Roger Koenker and Gilbert Bassett(1978) (13) pointed out how conditional quantiles could be estimated by an optimization function minimizing a sum of weighted absolute deviations, using weights as asymmetric functions of the quantiles.

In addition ,Koenker(1978) (13) supported that quantile regression offers considerable flexibility in empirical research since it disposes with the common slope assumption by allowing the effect of a change in a predictor variable to vary along the conditional distribution of Y.In particular, with a quantile regression, an analyst estimates a linear relationship between the covariates and a specified quantile of Y.Actually, the quantile regression model according to Roger Koenker and Kevin F. Hallock(2001) (14) can be viewed as a generalization of OLS to a collection of models with different conditional quantile functions.

3.5 Quantile regression:Intuition

Let Y be a real-valued random variable with cumulative distribution function:

$$F_Y(y) = P(Y \leq y) \tag{3.1}$$

The τth quantile of Y is given by:

$$Q_Y(\tau) = F_Y^{-1}(\tau) = \inf\{y : F_Y(y) \geq \tau\} \tag{3.2}$$

where $\tau \in (0, 1)$.

Define the loss function as:

$$\rho_\tau(y) = y(\tau - I_{(y<0)}) \tag{3.3}$$

where I is an indicator function. A specific quantile can be found by minimizing the expected loss of Y-u with respect to u

$$\min_u E(\rho_\tau(Y - u)) = \min_u \left\{ (\tau - 1) \int_{-\infty}^{u} (y - u) dF_Y(y) + \tau \int_{u}^{\infty} (y - u) dF_Y(y) \right\}. \tag{3.4}$$

This can be shown by setting the derivative of the expected loss function to 0 and letting q_τ be the solution of

$$0 = (1 - \tau) \int_{-\infty}^{q_\tau} dF_Y(y) - \tau \int_{q_\tau}^{\infty} dF_Y(y). \tag{3.5}$$

This equation reduces to

$$0 = F_Y(q_\tau) - \tau, \tag{3.6}$$

and then to

$$F_Y(q_\tau) = \tau. \tag{3.7}$$

Hence $q_\tau\ is \tau$th quantile of the random variable Y.

Consider $\tau = 0.5$ and let q be an initial guess forq_τ.The expected loss evaluated at q is

$L(q) = -0.5 \int_{-\infty}^{q} (y-q)dF_Y(y) + 0.5 \int_{q}^{\infty} (y-q)dF_Y(y).$

In order to minimize the expected loss, we move the value of q a little bit to see whether the expected loss will rise or fall. Suppose we increase q by 1 unit. Then the change of expected loss would be

$\int_{-\infty}^{q} 1dF_Y(y) - \int_{q}^{\infty} 1dF_Y(y).$

The first term of the equation is $F_Y(q)$ and second term of the equation is $1 - F_Y(q)$. Therefore, the change of expected loss function is negative if and only if $F_Y(q) < 0.5$, that is if and only if q is smaller than the median.Similarly, if we reduce q by 1 unit, the change of expected loss function is negative if and only if q is larger than the median.

In order to minimize the expected loss function, we would increase (decrease) L(q) if q is smaller (larger) than the median, until q reaches the median. The idea behind the minimization is to count the number of points (weighted with the density) that are larger or smaller than q and then move q to a point where q is larger than $100\tau\%$.

To sum up, it is worth to mention that quantile regression has a lot of advantages and this is why a lot of researchers prefer to base their analysis in this method.In more detail, quantile regression model(QRM) is well suited for capturing a potentially non-linear relationship between Y and X globally (i.e. over the entire conditional distribution of the dependent variable).In addition, it does not require any a priori assumptions about the distribution of errors, thus, it is not prone to misspecification.

This does not happen, for example, in OLS which is inefficient when the assumption of spherical disturbances is violated.So, quantile regression model(QRM) is robust to non-normal errors and to outliers.Finally,the QRM estimator is asymptotically normal with an analytical variance-covariance estimator (VCE) and it is invariant to monotonic transformations of the data. The only censored for quantile regression model is that estimated values can be obtained without making any distributional assumptions, but at the cost of computational difficulty, some of which can be avoided by using a simple three step censored quantile regression procedure as an approximation.

4 Results

4.1 Descriptive Statistics

Table 4.1: Descriptive Statistics for tsn-hrl

Statistics	Tdlnclose	Tdlnvol	Hdlnclose	Hdlnvol
mean	0.0007	0.00009	0.0005	0.00009
sd	0.02	0.40	0.012	0.39
median	0.001	-0.02	0.001	-0.01
min	-0.16	-1.29	-0.089	-1.65
max	0.10	2.31	0.06	1.51
skew	-0.60	0.47	-0.55	0.069
kurtosis	9.10	1.68	4.44	0.86
se	0.0003	0.01	0.0002	0.0082
tests	p-value	p-value	p-value	p-value
skewness	<0.01	<0.01	<0.01	<0.01
normality	<0.01	<0.01	<0.01	<0.01
kurtosis	<0.01	<0.01	<0.01	<0.01

The previous table summarizes descriptive coefficients of our data and includes measures of central tendency like the mean, median and measures of variability like the minimum and maximum variables and kurtosis skewness.In more details, tables 4.1 and 4.2 present descriptive statistics for the rates of change (returns) of prices and volumes.According to results there are no extreme values as min and max show.Furthermore, all price returns and volume returns show a positive and

Table 4.2: Descriptive Statistics for cag-syy

Statistics	Cdlnclose	Cdlnvol	Sdlnclose	Sdlnvol
mean	0.0002	0.0001	0.0004	-0.0005
sd	0.014	0.4	0.01	0.4
median	0.00039	-0.01	0.0005	-0.01
min	-0.18	-1.46	-0.099	-1.67
max	0.12	1.97	0.1	3.05
skew	-1.35	0.37	0.24	0.44
kurtosis	22.7	1.3	15.86	2.6
se	0.0002	0.0084	0.0002	0.0084

tests	p-value	p-value	p-value	p-value
skewness	<0.01	<0.01	<0.01	<0.01
normality	<0.01	<0.01	<0.01	<0.01
kurtosis	<0.01	<0.01	<0.01	<0.01

statistically significant kurtosis pointing to leptokurtic underlying distributions and no firm is an exception to that.In addition, taking into consideration tests of skewness(Agostino test),normality(Jarque-Bera test) and kurtosis, it turns out that the null hypothesis of normality is strongly rejected and alternative hypothesis is greater. As far as price returns for TSN,HRL and CAG concerned, they have negative and statistically significant skewness while price returns for Sysco have positive and statistically significance.Finally,volume returns in all cases exhibit positive and statistically significant skewness.

4.2 The empirical results

The following tables present the results of quantile regression analysis for positive and negative price returns and they also show the results obtained from the total sample.

According to 4.3 ,4.4 ,4.5 ,4.6 the results have shown that under positive price returns the slopes are positive at both low quantiles of volume changes and high quantiles.On the other hand, under negative price returns the slopes are negative at

Table 4.3: TSN:Quantile regression results

Quantile	dlnclose>0	dlnclose<0	Total sample
0.1	6.97	-12.75	0.4
0.2	7.31	-13.93	-1.32
0.3	7.13	-14.62	-1.76
0.4	9.09	-14.59	-1.67
0.5	9.36	-14.33	-0.99
0.6	11.86	-14.92	-1.79
0.7	12	-15	-1.72
0.8	12.79	-16.1	-2.53
0.9	12.91	-17.6	0.49

Table 4.4: HRL:Quantile regression results

Quantile	dlnclose>0	dlnclose<0	Total sample
0.1	6.76	-12.58	-2.51
0.2	7.35	-11.6	-2.11
0.3	9.26	-11	-2.62
0.4	11.92	-11.61	-1.54
0.5	12.24	-11.7	-2.2
0.6	12	-14.51	-2.22
0.7	13.89	-14.97	-2.93
0.8	13.97	-15.63	-1.96
0.9	14.17	-15.64	0.49

both low quantiles of volume changes and high quantiles.These results represent all firms (Tyson.Hormel Foods Corporation, Sysco Corporationand Conagra Brands) without an exception.In both cases,it is noticed a strongly significance in low and high quantiles.So,the null hypothesis of global equality of slopes is strongly rejected and there is no symmetry.

In addition, as far as the co-movement concern the general picture that it is noticed from comparing 4.3 , 4.4 , 4.5 , 4.6 is that there is a co-movement at the low and high quantiles of the dependent variable, something that indicates that there is correlation between closing price returns and volume trade.In other words, there is positive co-movement for positive price returns at the higher quantiles while at the same time there is negative co-movement for negative price returns at the higher quantiles.

Furthermore, while the level of quantiles increases, the intensity of co-movement

Table 4.5: CAG:Quantile regression results

Quantile	dlnclose>0	dlnclose<0	Total sample
0.1	9.87	-6.62	-2.21
0.2	9.39	-7.51	-1.79
0.3	9.74	-10.35	-2.22
0.4	11.13	-9.67	-2.28
0.5	13.3	-11.36	-1.67
0.6	13.11	-12.63	-0.62
0.7	13.52	-13.29	-0.59
0.8	14.06	-16.39	-0.97
0.9	14.08	-16.96	0.47

increases with stable but not extreme rhythm for both positive and negative price returns.

After that in order to enhance our results, we present some plots which show the coefficient. Figures 4.1 , 4.2 , 4.3 , 4.4 , 4.5 , 4.6 , 4.7 , 4.8 show there is a solid red line which is the OLS regression coefficient while at the same time dashed red lines are the confidence intervals around the OLS.Each black dot is the slope coefficient for the quantile indicated on the x-axis. The light gray area around the black dots is the confidence interval around the quantile.

Table 4.6: SYY:Quantile regression results

Quantile	dlnclose>0	dlnclose<0	Total sample
0.1	11.04	-12.84	-3.23
0.2	13.11	-12.38	-2.83
0.3	12.08	-14.74	-2.67
0.4	11.49	-15.35	-3.42
0.5	12.53	-17.29	-3.6
0.6	12.76	-19.22	-2.76
0.7	13.08	-19.77	-2.24
0.8	16.81	-20.49	-2.36
0.9	20.09	-20.29	0.48

The lower quantiles have significant difference below the OLS when price returns are positive, and the upper quantiles have significant difference above the OLS when price returns are negative.Specifically, all these figures confirm, as it is already mentioned, that there is positive co-movement for positive price returns at the higher

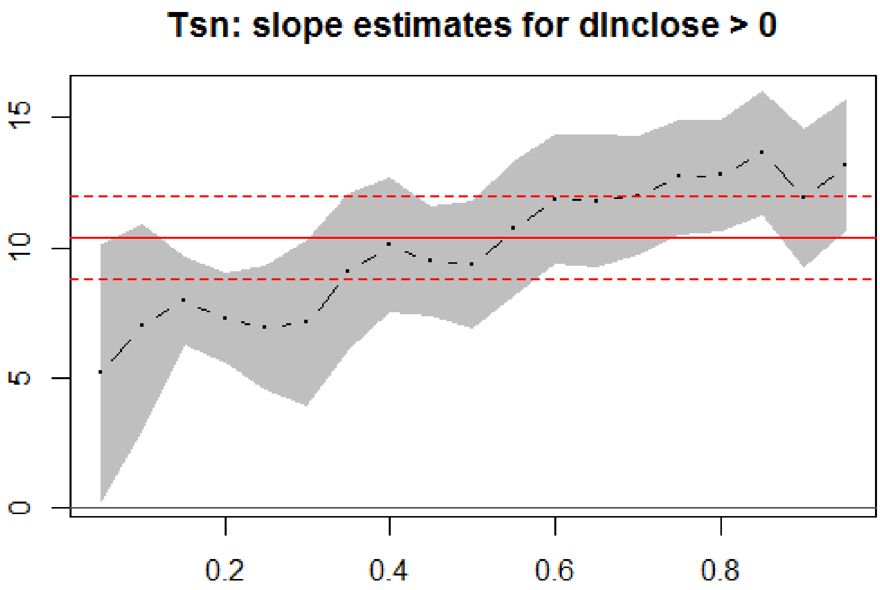

Figure 4.1: Tsn:slope estimates for dlnclose>0

quantiles while at the same time there is negative co-movement for negative price returns at the higher quantiles.

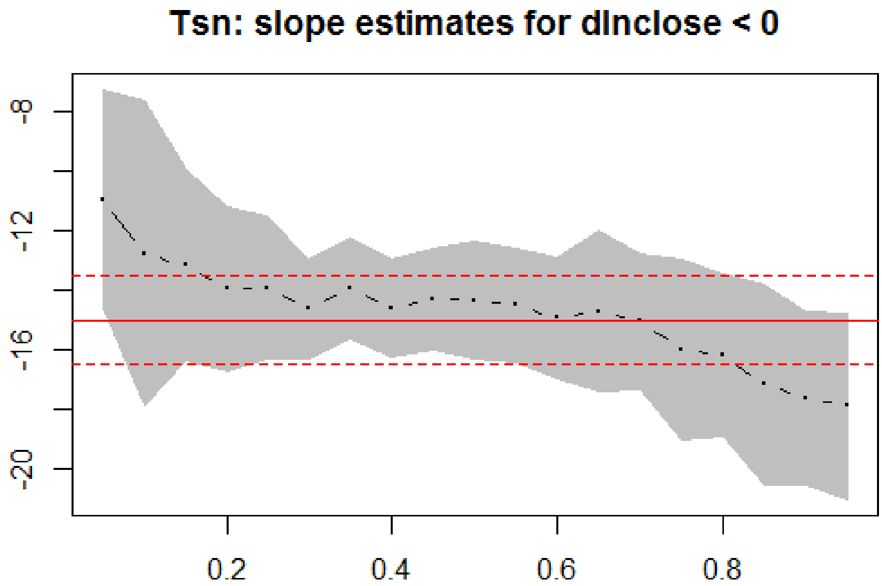

Figure 4.2: Tsn:slope estimates for dlnclose<0

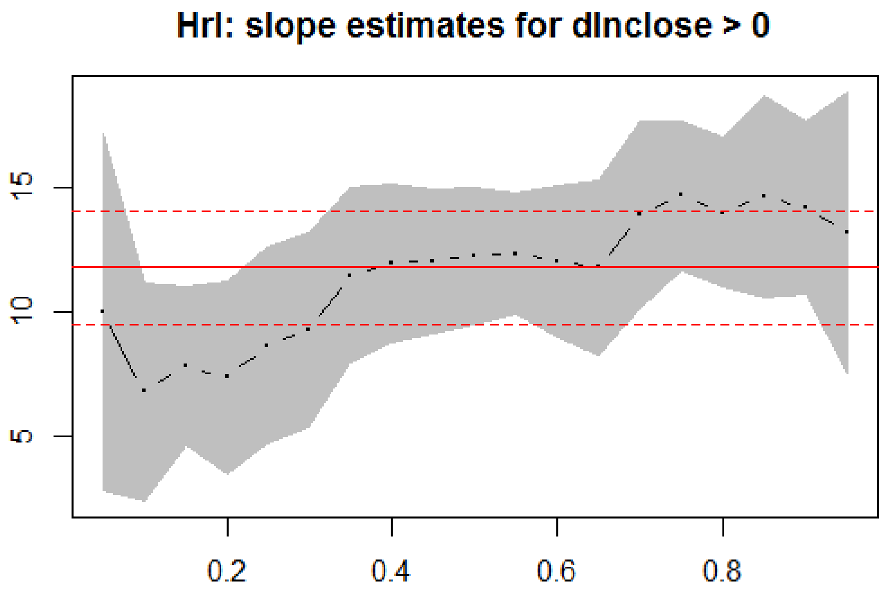

Figure 4.3: Hrl:slope estimates for dlnclose>0

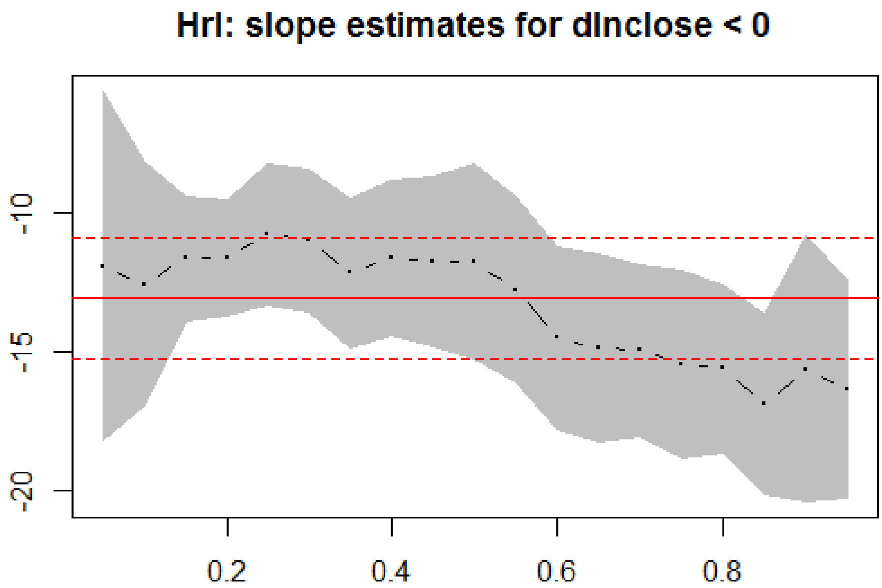

Figure 4.4: Hrl:slope estimates for dlnclose<0

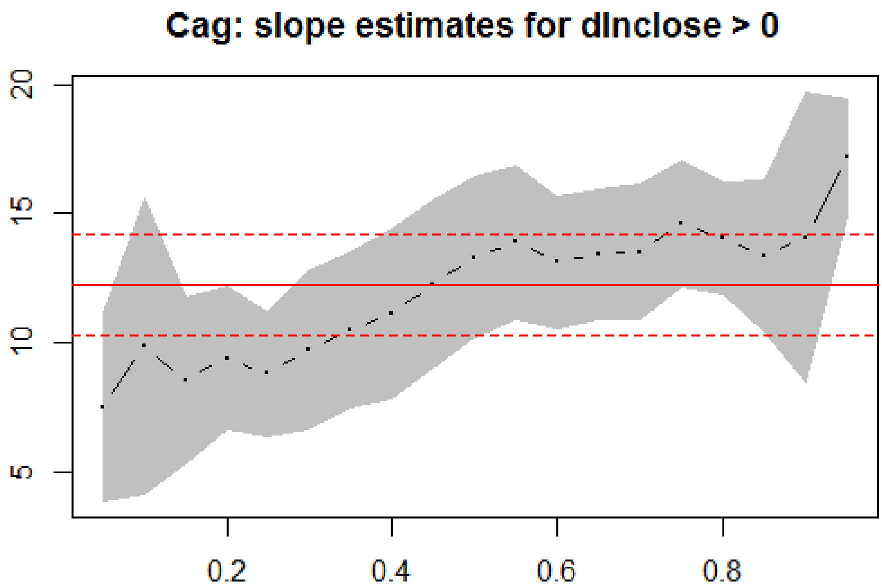

Figure 4.5: Cag:slope estimates for dlnclose>0

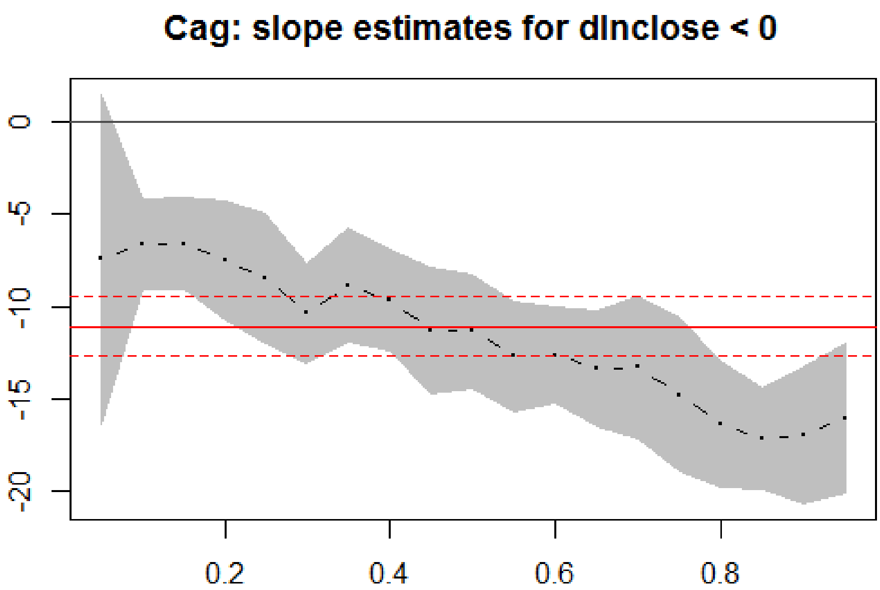

Figure 4.6: Cag:slope estimates for dlnclose<0

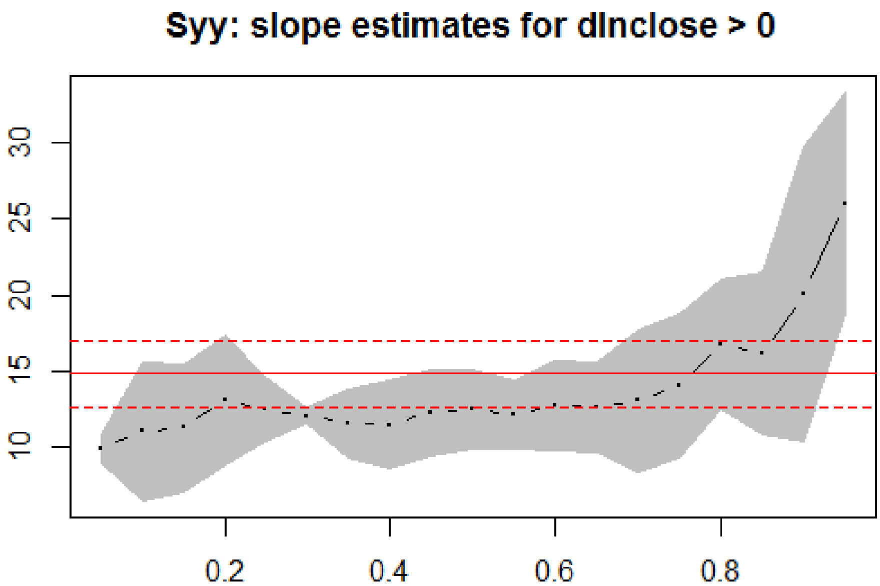

Figure 4.7: Syy:slope estimates for dlnclose>0

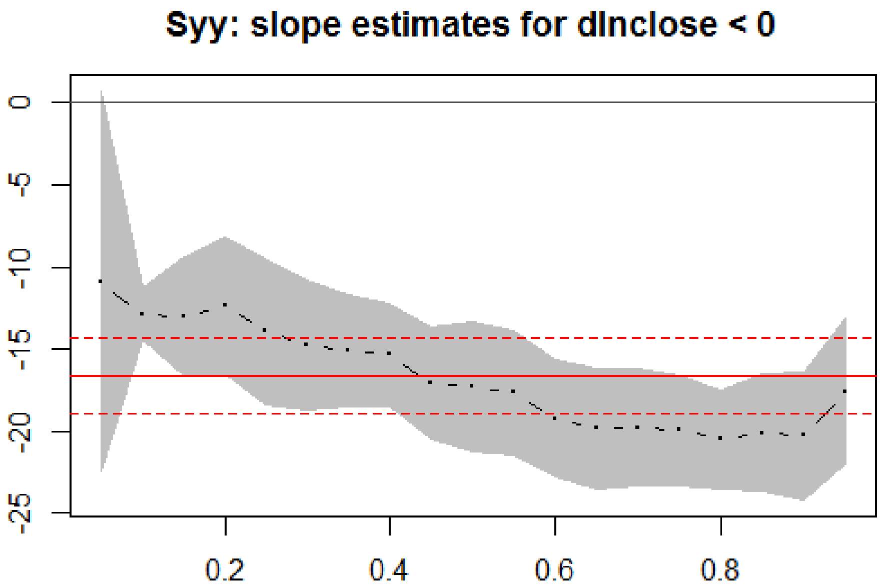

Figure 4.8: Syy:slope estimates for dlnclose<0

5 Conclusion

5.1 Conclusion

The objective of the present study is to investigate the relationship between closing price returns and volume trade.This is why it utilized daily data on closing prices and volumes for meat packaging and processing firms over 2009 to 2019.

The empirical results have shown that there is correlation between price returns and volume changes for positive and negative price returns.In more detail, there is a co-movement at the low and high quantiles of the dependent variable and more specifically, a positive co-movement for positive price returns at the higher quantiles and negative co-movement for negative price returns at the higher quantiles.

Moreover, the intensity of co-movement shows a tendency to rise while the level of quantile increases.This means that in both positive and negative quantiles the intensity of co-movement increases while the level of quantiles increases. These results are consistent with M.Karpoff(1987) (12) who argued that volume is positively related to the magnitude of the price change and, in equity markets, to the price change.In addition, the findings are a little differentiated with Yi-Chiuan Wang and Yi Hao Lai (21) who found that extreme high volumes tend to synchronize with both extreme high and extreme low returns.

In each case, researchers are willing to study and to investigate the linkage between the closing price and volume trade.So, it is reasonable that a lot of researches happens and will continue to happen because the topic is very interesting.Therefore, the researches that will follow are certainly warranted because the topic is elaborated.

6

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(1? –21)

Appendix A

A.1 Agostino test

In statistics, D'Agostino's K2 test, named for Ralph D'Agostino, is a goodness-of-fit measure of departure from normality, that is the test aims to establish whether or not the given sample comes from a normally distributed population. The test is based on transformations of the sample kurtosis and skewness and has power only against the alternatives that the distribution is referred to skewness or kurtosis.

A.2 Jarque–Bera test

In statistics, the Jarque–Bera test is a goodness-of-fit test of whether sample data have the skewness and kurtosis matching a normal distribution. The test is named after Carlos Jarque and Anil K. Bera. The test statistic is always nonnegative. If it is far from zero, it signals the data do not have a normal distribution.

A.3 Skewness and kurtosis

Skewness is a measure of symmetry, or more precisely, the lack of symmetry. A distribution, or data set, is symmetric if it looks the same to the left and right of the center point.

Kurtosis is a measure of whether the data are heavy-tailed or light-tailed relative to a normal distribution. That is, data sets with high kurtosis tend to have heavy tails or outliers. Data sets with low kurtosis tend to have light tails, or lack of outliers. A uniform distribution would be the extreme case.

Appendix B

This part contains supplementary data and cite the way that the data are downloaded by using a code in R.First of all, it is necessary to install the following packages and libraries:

B.1 Installing R packages

```
install.packages('tidyverse', dep = TRUE)
install.packages('tidyquant', dep = TRUE)
install.packages('fredr', dep = TRUE)
install.packages('quantl', dep = TRUE)
install.packages('ggthemes', dep = TRUE)
install.packages('ggplot2', dep = TRUE)
install.packages('ggrepel', dep = TRUE)
install.packages('readr', dep = TRUE)
install.packages('tidyr', dep = TRUE)
install.packages('lubridate', dep = TRUE)
install.packages('DT', dep = TRUE)
install.packages('scatterplot3d', dep = TRUE)
install.packages('Hmisc', dep = TRUE)
install.packages('pastecs', dep = TRUE)
install.packages('xtable', dep = TRUE)
```

B.2 Installing R libraries

```
library(tidyverse, dep = TRUE)
library(tidyquant, dep = TRUE)
library(fredr, dep = TRUE)
library(Quandl, dep = TRUE)
library(ggthemes, dep= TRUE)
library(ggplot2, dep= TRUE)
library(ggrepel, dep = TRUE)
library(readr, dep = TRUE)
library(tidyr, dep = TRUE)
library(lubridate, dep = TRUE)
library(DT, dep = TRUE)
library(scatterplot3d, dep = TRUE)
library(Hmisc, dep = TRUE)
library(pastecs, dep = TRUE)
library(xtable, dep = TRUE)
```

B.3 Download data from Yahoo Finance

After that we use ”Yahoo Finance” which is a data frame with free stock quotes.Firms’ data that are downloaded from ”Yahoo Finance” represent daily values and every firm contains the open, close, high and low value and the shareholder volume. All data have been downloaded by the following commands:

```

Start_Date <- "2009-11-01"

hrl_d <- tq_get("HRL", from = Start_Date)
```

```
tsn_d <- tq_get("TSN", from = Start_Date)
cag_d <- tq_get("CAG", from = Start_Date)
syy_d <- tq_get("SYY", from = Start_Date)
```

Our analysis focuses in a decade and specifically starts from the 1st of November 2009 until the 31st of October 2019.The command in order to download data starting from this period is:

```
Start_Date2010 <- as.Date("2009-11-01")
```

B.4 Data Transformations

Then it is necessary to make some useful transformations which will help us in our analysis.In other words, we need logarithms of prices and volumes for firms and this is achieved by using the following command:

```
cag_d <- cag_d %>%
  mutate(dln_close = c(NA, diff(log(close))))
cag_d <- cag_d %>%
  mutate(dln_volume = c(NA, diff(log(volume))))
cag_d2010 <- cag_d %>%
  filter(date >= Start_Date2010)

tsn_d <- tsn_d %>%
  mutate(dln_close = c(NA, diff(log(close))))
tsn_d <- tsn_d %>%
  mutate(dln_volume = c(NA, diff(log(volume))))
tsn_d2010 <- tsn_d %>%
  filter(date >= Start_Date2010)

syy_d <- syy_d %>%
```

```
  mutate(dln_close = c(NA, diff(log(close))))
syy_d <- syy_d %>%
  mutate(dln_volume = c(NA, diff(log(volume))))
syy_d2010 <- syy_d %>%
  filter(date >= Start_Date2010)

hrl_d <- hrl_d %>%
  mutate(dln_close = c(NA, diff(log(close))))
hrl_d <- hrl_d %>%
  mutate(dln_volume = c(NA, diff(log(volume))))
hrl_d2010 <- hrl_d %>%
  filter(date >= Start_Date2010)
```

B.5 Save Data

Finally, in order to save all data we use the following command in R:

```
 babis<-" hrl_d, tsn_d, cag_d, syy_d"
save(babis,file = "babis.Rda", hrl_d,  tsn_d, cag_d, syy_d)
```

Appendix C

C.1 Quantile Regression

```
taf=c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9)


for (i in 1:1){
  #### cag ####

   j<-1

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010, dln_
    close>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
   x<-as.data.frame(summary(RQ)$coefficients)
   x$tau<-summary(RQ)$tau
   x$explanation<-"cag_d2010 dln_close dln_volume & dln_close>0"
   warn<-warnings()

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010, dln_
    close<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
   x1<-as.data.frame(summary(RQ)$coefficients)
   x1$tau<-summary(RQ)$tau
   x1$explanation<-"cag_d2010 dln_close dln_volume & dln_close<0"
```

```
x<-rbind(x,x1)
warn<-c(warn,warnings())

RQ <- rq(dln_volume ~ dln_close, data=cag_d2010,tau = taf[j], method
  = "br", ci = TRUE, iid = TRUE)
x1<-as.data.frame(summary(RQ)$coefficients)
x1$tau<-summary(RQ)$tau
x1$explanation<-"cag_d2010 dln_close dln_volume"
x<-rbind(x,x1)
warn<-c(warn,warnings())


cag_dlnclose_control<-as.data.frame(x)



for (j in 2:9){
  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010,
  dln_close>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x<-as.data.frame(summary(RQ)$coefficients)
  x$tau<-summary(RQ)$tau
  x$explanation<-"cag_d2010 dln_close dln_volume & dln_close>0"
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010,
  dln_close<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"cag_d2010 dln_close dln_volume & dln_close<0"
  x<-rbind(x,x1)
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data=cag_d2010,tau = taf[j],
  method = "br", ci = TRUE, iid = TRUE)
```

```
    x1<-as.data.frame(summary(RQ)$coefficients)
    x1$tau<-summary(RQ)$tau
    x1$explanation<-"cag_d2010 dln_close dln_volume"
    x<-rbind(x,x1)
    warn<-c(warn,warnings())

    cag_dlnclose_control<-rbind(cag_dlnclose_control,x)
  }
  warn<-c(warn,warnings())

  j<-1

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010, dln_volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x<-as.data.frame(summary(RQ)$coefficients)
  x$tau<-summary(RQ)$tau
  x$explanation<-"cag_d2010 dln_volume dln_close & dln_volume>0"
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010, dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"cag_d2010 dln_volume dln_close & dln_volume<0"
  x<-rbind(x,x1)
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data=cag_d2010,tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"cag_d2010 dln_volume dln_close"
  x<-rbind(x,x1)
  warn<-c(warn,warnings())
```

```
cag_dlnvolume_control<-as.data.frame(x)


for (j in 2:9){
  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010,
  dln_volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x<-as.data.frame(summary(RQ)$coefficients)
  x$tau<-summary(RQ)$tau
  x$explanation<-"cag_d2010 dln_volume dln_close & dln_volume>0"
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010,
  dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"cag_d2010 dln_volume dln_close & dln_volume<0"
  x<-rbind(x,x1)
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data=cag_d2010,tau = taf[j],
  method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"cag_d2010 dln_volume dln_close"
  x<-rbind(x,x1)
  warn<-c(warn,warnings())

  cag_dlnvolume_control<-rbind(cag_dlnvolume_control,x)
}
warn<-c(warn,warnings())

#### tsn ####
```

```
j<-1

RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010, dln_close>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
x<-as.data.frame(summary(RQ)$coefficients)
x$tau<-summary(RQ)$tau
x$explanation<-"tsn_d2010 dln_close dln_volume & dln_close>0"
warn<-c(warn,warnings())

RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010, dln_close<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
x1<-as.data.frame(summary(RQ)$coefficients)
x1$tau<-summary(RQ)$tau
x1$explanation<-"tsn_d2010 dln_close dln_volume & dln_close<0"
x<-rbind(x,x1)
warn<-c(warn,warnings())

RQ <- rq(dln_volume ~ dln_close, data=tsn_d2010,tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
x1<-as.data.frame(summary(RQ)$coefficients)
x1$tau<-summary(RQ)$tau
x1$explanation<-"tsn_d2010 dln_close dln_volume"
x<-rbind(x,x1)
warn<-c(warn,warnings())


tsn_dlnclose_control<-as.data.frame(x)



for (j in 2:9){
  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010, dln_close>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
```

```
    x<-as.data.frame(summary(RQ)$coefficients)
    x$tau<-summary(RQ)$tau
    x$explanation<-"tsn_d2010 dln_close dln_volume & dln_close>0"
    warn<-c(warn,warnings())

    RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010,
   dln_close<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
    x1<-as.data.frame(summary(RQ)$coefficients)
    x1$tau<-summary(RQ)$tau
    x1$explanation<-"tsn_d2010 dln_close dln_volume & dln_close<0"
    x<-rbind(x,x1)
    warn<-c(warn,warnings())

    RQ <- rq(dln_volume ~ dln_close, data=tsn_d2010,tau = taf[j],
   method = "br", ci = TRUE, iid = TRUE)
    x1<-as.data.frame(summary(RQ)$coefficients)
    x1$tau<-summary(RQ)$tau
    x1$explanation<-"tsn_d2010 dln_close dln_volume"
    x<-rbind(x,x1)
    warn<-c(warn,warnings())

    tsn_dlnclose_control<-rbind(tsn_dlnclose_control,x)
  }
  warn<-c(warn,warnings())

  j<-1

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010, dln_
   volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x<-as.data.frame(summary(RQ)$coefficients)
  x$tau<-summary(RQ)$tau
  x$explanation<-"tsn_d2010 dln_volume dln_close & dln_volume>0"
  warn<-c(warn,warnings())

```

```
RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010, dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
x1<-as.data.frame(summary(RQ)$coefficients)
x1$tau<-summary(RQ)$tau
x1$explanation<-"tsn_d2010 dln_volume dln_close & dln_volume<0"
x<-rbind(x,x1)
warn<-c(warn,warnings())

RQ <- rq(dln_volume ~ dln_close, data=tsn_d2010,tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
x1<-as.data.frame(summary(RQ)$coefficients)
x1$tau<-summary(RQ)$tau
x1$explanation<-"tsn_d2010 dln_volume dln_close"
x<-rbind(x,x1)
warn<-c(warn,warnings())


tsn_dlnvolume_control<-as.data.frame(x)


for (j in 2:9){
  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010, dln_volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x<-as.data.frame(summary(RQ)$coefficients)
  x$tau<-summary(RQ)$tau
  x$explanation<-"tsn_d2010 dln_volume dln_close & dln_volume>0"
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010, dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"tsn_d2010 dln_volume dln_close & dln_volume<0"
  x<-rbind(x,x1)
```

```
    warn<-c(warn,warnings())

    RQ <- rq(dln_volume ~ dln_close, data=tsn_d2010,tau = taf[j],
   method = "br", ci = TRUE, iid = TRUE)
    x1<-as.data.frame(summary(RQ)$coefficients)
    x1$tau<-summary(RQ)$tau
    x1$explanation<-"tsn_d2010 dln_volume dln_close"
    x<-rbind(x,x1)
    warn<-c(warn,warnings())

    tsn_dlnvolume_control<-rbind(tsn_dlnvolume_control,x)
 }
 warn<-c(warn,warnings())

 #### hrl ####

 j<-1

 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010, dln_
   close >0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
 x<-as.data.frame(summary(RQ)$coefficients)
 x$tau<-summary(RQ)$tau
 x$explanation<-"hrl_d2010 dln_close dln_volume & dln_close >0"
 warn<-c(warn,warnings())

 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010, dln_
   close <0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
 x1<-as.data.frame(summary(RQ)$coefficients)
 x1$tau<-summary(RQ)$tau
 x1$explanation<-"hrl_d2010 dln_close dln_volume & dln_close <0"
 x<-rbind(x,x1)
 warn<-c(warn,warnings())
```

```r
RQ <- rq(dln_volume ~ dln_close, data=hrl_d2010,tau = taf[j], method
 = "br", ci = TRUE, iid = TRUE)
x1<-as.data.frame(summary(RQ)$coefficients)
x1$tau<-summary(RQ)$tau
x1$explanation<-"hrl_d2010 dln_close dln_volume"
x<-rbind(x,x1)
warn<-c(warn,warnings())


hrl_dlnclose_control<-as.data.frame(x)



for (j in 2:9){
  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010,
  dln_close>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x<-as.data.frame(summary(RQ)$coefficients)
  x$tau<-summary(RQ)$tau
  x$explanation<-"hrl_d2010 dln_close dln_volume & dln_close>0"
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010,
  dln_close<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"hrl_d2010 dln_close dln_volume & dln_close<0"
  x<-rbind(x,x1)
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data=hrl_d2010,tau = taf[j],
  method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"hrl_d2010 dln_close dln_volume"
```

```
    x<-rbind(x,x1)
    warn<-c(warn,warnings())

    hrl_dlnclose_control<-rbind(hrl_dlnclose_control,x)
  }
  warn<-c(warn,warnings())

  j<-1

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010, dln_volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x<-as.data.frame(summary(RQ)$coefficients)
  x$tau<-summary(RQ)$tau
  x$explanation<-"hrl_d2010 dln_volume dln_close & dln_volume>0"
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010, dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"hrl_d2010 dln_volume dln_close & dln_volume<0"
  x<-rbind(x,x1)
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data=hrl_d2010,tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"hrl_d2010 dln_volume dln_close"
  x<-rbind(x,x1)
  warn<-c(warn,warnings())


  hrl_dlnvolume_control<-as.data.frame(x)
```

```
for (j in 2:9){
  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010,
  dln_volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x<-as.data.frame(summary(RQ)$coefficients)
  x$tau<-summary(RQ)$tau
  x$explanation<-"hrl_d2010 dln_volume dln_close & dln_volume>0"
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010,
  dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"hrl_d2010 dln_volume dln_close & dln_volume<0"
  x<-rbind(x,x1)
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data=hrl_d2010,tau = taf[j],
  method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"hrl_d2010 dln_volume dln_close"
  x<-rbind(x,x1)
  warn<-c(warn,warnings())

  hrl_dlnvolume_control<-rbind(hrl_dlnvolume_control,x)
}
warn<-c(warn,warnings())

#### syy ####

j<-1

```

```
RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010, dln_close>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
x<-as.data.frame(summary(RQ)$coefficients)
x$tau<-summary(RQ)$tau
x$explanation<-"syy_d2010 dln_close dln_volume & dln_close>0"
warn<-c(warn,warnings())

RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010, dln_close<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
x1<-as.data.frame(summary(RQ)$coefficients)
x1$tau<-summary(RQ)$tau
x1$explanation<-"syy_d2010 dln_close dln_volume & dln_close<0"
x<-rbind(x,x1)
warn<-c(warn,warnings())

RQ <- rq(dln_volume ~ dln_close, data=syy_d2010,tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
x1<-as.data.frame(summary(RQ)$coefficients)
x1$tau<-summary(RQ)$tau
x1$explanation<-"syy_d2010 dln_close dln_volume"
x<-rbind(x,x1)
warn<-c(warn,warnings())


syy_dlnclose_control<-as.data.frame(x)



for (j in 2:9){
  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010, dln_close>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x<-as.data.frame(summary(RQ)$coefficients)
  x$tau<-summary(RQ)$tau
  x$explanation<-"syy_d2010 dln_close dln_volume & dln_close>0"
```

```
    warn<-c(warn,warnings())

    RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010, dln_close<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
    x1<-as.data.frame(summary(RQ)$coefficients)
    x1$tau<-summary(RQ)$tau
    x1$explanation<-"syy_d2010 dln_close dln_volume & dln_close<0"
    x<-rbind(x,x1)
    warn<-c(warn,warnings())

    RQ <- rq(dln_volume ~ dln_close, data=syy_d2010,tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
    x1<-as.data.frame(summary(RQ)$coefficients)
    x1$tau<-summary(RQ)$tau
    x1$explanation<-"syy_d2010 dln_close dln_volume"
    x<-rbind(x,x1)
    warn<-c(warn,warnings())

    syy_dlnclose_control<-rbind(syy_dlnclose_control,x)
  }
  warn<-c(warn,warnings())

  j<-1

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010, dln_volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x<-as.data.frame(summary(RQ)$coefficients)
  x$tau<-summary(RQ)$tau
  x$explanation<-"syy_d2010 dln_volume dln_close & dln_volume>0"
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010, dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
```

```
x1$tau<-summary(RQ)$tau
x1$explanation<-"syy_d2010 dln_volume dln_close & dln_volume<0"
x<-rbind(x,x1)
warn<-c(warn,warnings())

RQ <- rq(dln_volume ~ dln_close, data=syy_d2010,tau = taf[j], method
  = "br", ci = TRUE, iid = TRUE)
x1<-as.data.frame(summary(RQ)$coefficients)
x1$tau<-summary(RQ)$tau
x1$explanation<-"syy_d2010 dln_volume dln_close"
x<-rbind(x,x1)
warn<-c(warn,warnings())


syy_dlnvolume_control<-as.data.frame(x)


for (j in 2:9){
  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010,
  dln_volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x<-as.data.frame(summary(RQ)$coefficients)
  x$tau<-summary(RQ)$tau
  x$explanation<-"syy_d2010 dln_volume dln_close & dln_volume>0"
  warn<-c(warn,warnings())

  RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010,
  dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
  x1<-as.data.frame(summary(RQ)$coefficients)
  x1$tau<-summary(RQ)$tau
  x1$explanation<-"syy_d2010 dln_volume dln_close & dln_volume<0"
  x<-rbind(x,x1)
  warn<-c(warn,warnings())

```

```
    RQ <- rq(dln_volume ~ dln_close , data=syy_d2010,tau = taf[j],
   method = "br", ci = TRUE, iid = TRUE)
    x1<-as.data.frame(summary(RQ)$coefficients)
    x1$tau<-summary(RQ)$tau
    x1$explanation<-"syy_d2010 dln_volume dln_close"
    x<-rbind(x,x1)
    warn<-c(warn,warnings())

    syy_dlnvolume_control<-rbind(syy_dlnvolume_control,x)
  }
  warn<-c(warn,warnings())
```

C.2 Descriptive Statistics

Useful libraries:

```
library(moments)
library(normtest)
```

Descriptive statistics is a branch of statistics that aims at describing a number of features of data usually involved in a study.The code that is used for descriptive statistics is:

```
## Descriptive Statistics per firm

TSN_d.Y <- diff("tsn_d2010")
describe(tsn_d2010)
x<- describe(tsn_d2010)
x<-x[8:9,]
x = subset(x, select = -c(vars,n,trimmed,range,mad) )
t_x <- transpose(x)
```

```
colnames(t_x) <- rownames(x)
rownames(t_x) <- colnames(x)
xtable_tsn<-xtable(t_x)
#isna<-table(is.na(x))
warn<-c(warn,warnings())

t_table<-as.data.frame(t_x)

HRL_d.Y <- diff("hrl_d2010")
describe(hrl_d2010)
x<- describe(hrl_d2010)
x<-x[8:9,]
x = subset(x, select = -c(vars,n,trimmed,range,mad) )
t_x <- transpose(x)
colnames(t_x) <- rownames(x)
rownames(t_x) <- colnames(x)
xtable_hrl<-xtable(t_x)
#isna<-table(is.na(x))
warn<-c(warn,warnings())

t_table<-cbind(t_table,t_x)

CAG_d.Y <- diff("cag_d2010")
describe(cag_d2010)
x<- describe(cag_d2010)
x<-x[8:9,]
x = subset(x, select = -c(vars,n,trimmed,range,mad) )
t_x <- transpose(x)
colnames(t_x) <- rownames(x)
rownames(t_x) <- colnames(x)
xtable_cag<-xtable(t_x)
#isna<-table(is.na(x))
warn<-c(warn,warnings())
```

```
t_table<-cbind(t_table,t_x)

SYY_d.Y <- diff("syy_d2010")
describe(syy_d2010)
x<- describe(syy_d2010)
x<-x[8:9,]
x = subset(x, select = -c(vars,n,trimmed,range,mad) )
t_x <- transpose(x)
colnames(t_x) <- rownames(x)
rownames(t_x) <- colnames(x)
xtable_syy<-xtable(t_x)
#isna<-table(is.na(x))
warn<-c(warn,warnings())

t_table<-cbind(t_table,t_x)
```

```
## Tests

##https://cran.r-project.org/web/packages/moments/moments.pdf
library(moments)
library(normtest)


dlnp<-cag_d2010$dln_close
skewness(dlnp)
### skewness
agostino.test(dlnp, alternative = c("two.sided", "less", "greater"))

### normality
jarque.test(dlnp)

#kurtosis
kurtosis(dlnp, na.rm = FALSE)
```

```
moment(dlnp, order = 1, central = FALSE, absolute = FALSE, na.rm =
    FALSE)

##https://www.rdocumentation.org/packages/normtest/versions/1.1/topics/
    kurtosis.norm.test
kurtosis.norm.test(dlnp, nrepl=2000)
```

C.3 Daily plots: Code

At the beginning we load our data, and some "libraries" that are useful:

```
load("babis.Rda")
```

```
library(plotly)
library(reshape2)
```

Here we cite code for plots. These plots concern daily data and more specifically plots which include logarithm close price and volume for firms.The commands are the following:

```
library(SciViews)

## daily logarithm close price and volume
###                                   TSN
dftogether<-data.frame(tsn_d$date, tsn_d$close, tsn_d$volume)
dftogether$ln_close<-ln(dftogether$tsn_d.close)
dftogether$ln_volume<-ln(dftogether$tsn_d.volume)

p <- ggplot(dftogether, aes(x = dftogether$tsn_d.date))
```

```
p <- p + geom_line(aes(y = ln_volume/3.9, colour = "ln_volume"),alpha=1
    /1.5)
p <- p + geom_line(aes(y = ln_close, colour = "ln_close"))
p <- p + scale_y_continuous(sec.axis = sec_axis(~.*3.9, name = "ln
    volume"))
p <- p + scale_colour_manual(values = c("blue", "red"))
p <- p + labs(y = "ln close",
              x = "Date",
              colour = "tsn")
##p <- p + theme(legend.position = c(0.8, 0.9))
p

###                           HRL
dftogether<-data.frame(hrl_d$date,hrl_d$close,hrl_d$volume)
dftogether$ln_close<-ln(dftogether$hrl_d.close)
dftogether$ln_volume<-ln(dftogether$hrl_d.volume)

p <- ggplot(dftogether, aes(x = dftogether$hrl_d.date))
p <- p + geom_line(aes(y = ln_volume/4.5, colour = "ln_volume"),alpha=1
    /1.5)
p <- p + geom_line(aes(y = ln_close, colour = "ln_close"))
p <- p + scale_y_continuous(sec.axis = sec_axis(~.*4.5, name = "ln
    volume"))
p <- p + scale_colour_manual(values = c("blue", "red"))
p <- p + labs(y = "ln close",
              x = "Date",
              colour = "hrl")
##p <- p + theme(legend.position = c(0.8, 0.9))
p

###                           CAG

dftogether<-data.frame(cag_d$date,cag_d$close,cag_d$volume)
dftogether$ln_close<-ln(dftogether$cag_d.close)
```

```
dftogether$ln_volume<-ln(dftogether$cag_d.volume)

p <- ggplot(dftogether, aes(x = dftogether$cag_d.date))
p <- p + geom_line(aes(y = ln_volume/4.5, colour = "ln_volume"),alpha=1/1.5)
p <- p + geom_line(aes(y = ln_close, colour = "ln_close"))
p <- p + scale_y_continuous(sec.axis = sec_axis(~.*4.5, name = "ln volume"))
p <- p + scale_colour_manual(values = c("blue", "red"))
p <- p + labs(y = "ln close",
              x = "Date",
              colour = "cag")
##p <- p + theme(legend.position = c(0.8, 0.9))
p


###                     SYY
dftogether<-data.frame(syy_d$date,syy_d$close,syy_d$volume)
dftogether$ln_close<-ln(dftogether$syy_d.close)
dftogether$ln_volume<-ln(dftogether$syy_d.volume)

p <- ggplot(dftogether, aes(x = dftogether$syy_d.date))
p <- p + geom_line(aes(y = ln_volume/3.9, colour = "ln_volume"),alpha=1/1.5)
p <- p + geom_line(aes(y = ln_close, colour = "ln_close"))
p <- p + scale_y_continuous(sec.axis = sec_axis(~.*3.9, name = "ln volume"))
p <- p + scale_colour_manual(values = c("blue", "red"))
p <- p + labs(y = "ln close",
              x = "Date",
              colour = "syy")
##p <- p + theme(legend.position = c(0.8, 0.9))
p
```

C.4 Slope Estimates

```
##Plots
##                              TSN
mydata<-tsn_d2010
keeps<-c("date","dln_volume","dln_close")
mydata<-mydata[keeps]
names(mydata)<-c("date","Y","X")


#### Plotting data_Positive
    quantreg.all.pos <- rq(Y ~ X, data=filter(mydata, X>0), tau = seq
     (0.05, 0.95, by = 0.05))
    quantreg.plot.pos <- summary(quantreg.all.pos)
    plot(quantreg.plot.pos, parm=2, main="tsn: slope estimates for
     dlnclose > 0")

#### Plotting data_Negative
    quantreg.all.neg <- rq(Y ~ X, data=filter(mydata, X<0), tau = seq
     (0.05, 0.95, by = 0.05))
    quantreg.plot.neg <- summary(quantreg.all.neg)
    plot(quantreg.plot.neg,  parm=2, main="tsn: slope estimates for
     dlnclose < 0")

 ##                              HRL
 mydata<-hrl_d2010
keeps<-c("date","dln_volume","dln_close")
mydata<-mydata[keeps]
names(mydata)<-c("date","Y","X")


#### Plotting data_Positive
```

```
    quantreg.all.pos <- rq(Y ~ X, data=filter(mydata, X>0), tau = seq
    (0.05, 0.95, by = 0.05))
    quantreg.plot.pos <- summary(quantreg.all.pos)
    plot(quantreg.plot.pos, parm=2, main="hrl: slope estimates for
    dlnclose > 0")

#### Plotting data_Negative
    quantreg.all.neg <- rq(Y ~ X, data=filter(mydata, X<0), tau = seq
    (0.05, 0.95, by = 0.05))
    quantreg.plot.neg <- summary(quantreg.all.neg)
    plot(quantreg.plot.neg,  parm=2, main="hrl: slope estimates for
    dlnclose < 0")


 ##                          CAG
 mydata<-cag_d2010
keeps<-c("date","dln_volume","dln_close")
mydata<-mydata[keeps]
names(mydata)<-c("date","Y","X")


#### Plotting data_Positive
    quantreg.all.pos <- rq(Y ~ X, data=filter(mydata, X>0), tau = seq
    (0.05, 0.95, by = 0.05))
    quantreg.plot.pos <- summary(quantreg.all.pos)
    plot(quantreg.plot.pos, parm=2, main="cag: slope estimates for
    dlnclose > 0")

#### Plotting data_Negative
    quantreg.all.neg <- rq(Y ~ X, data=filter(mydata, X<0), tau = seq
    (0.05, 0.95, by = 0.05))
    quantreg.plot.neg <- summary(quantreg.all.neg)
    plot(quantreg.plot.neg,  parm=2, main="cag: slope estimates for
    dlnclose < 0")
```

```
##                    SYY
 mydata<-syy_d2010
keeps<-c("date","dln_volume","dln_close")
mydata<-mydata[keeps]
names(mydata)<-c("date","Y","X")


#### Plotting data_Positive
   quantreg.all.pos <- rq(Y ~ X, data=filter(mydata, X>0), tau = seq
    (0.05, 0.95, by = 0.05))
   quantreg.plot.pos <- summary(quantreg.all.pos)
   plot(quantreg.plot.pos, parm=2, main="syy: slope estimates for
    dlnclose > 0")

#### Plotting data_Negative
   quantreg.all.neg <- rq(Y ~ X, data=filter(mydata, X<0), tau = seq
    (0.05, 0.95, by = 0.05))
   quantreg.plot.neg <- summary(quantreg.all.neg)
   plot(quantreg.plot.neg,  parm=2, main="syy: slope estimates for
    dlnclose < 0")
```