



UNIVERSITY OF IOANNINA

DEPARTMENT OF ECONOMICS

MSC IN ECONOMIC ANALYSIS

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

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# Contents

<b>List of Tables</b>	<b>iii</b>
<b>List of Figures</b>	<b>v</b>
<b>Abstract</b>	<b>1</b>
0.1 Abstract . . . . .	1
<b>1 Introduction</b>	<b>3</b>
1.1 The impact of the stock market in the economy . . . . .	3
<b>2 Literature review</b>	<b>5</b>
2.1 Theoretical Background . . . . .	5
<b>3 Data and methodology</b>	<b>7</b>
3.1 Data collection . . . . .	7
3.2 Daily plots . . . . .	7
3.3 Methodology:what is quantile regression . . . . .	9
3.4 Quantile regression:History . . . . .	10
3.5 Quantile regression:Intuition . . . . .	12
<b>4 Results</b>	<b>15</b>
4.1 Descriptive Statistics . . . . .	15
4.2 The empirical results . . . . .	16
<b>5 Conclusion</b>	<b>25</b>
5.1 Conclusion . . . . .	25
<b>6 Bibliography</b>	<b>27</b>
<b>Bibliography</b>	<b>29</b>

<b>A</b>	<b>Appendix A</b>	<b>A1</b>
A.1	Agostino test . . . . .	A1
A.2	Jarque–Bera test . . . . .	A1
A.3	Skewness and kurtosis . . . . .	A1
<b>B</b>	<b>Appendix B</b>	<b>A3</b>
B.1	Installing R packages . . . . .	A3
B.2	Installing R libraries . . . . .	A4
B.3	Download data from Yahoo Finance . . . . .	A4
B.4	Data Transformations . . . . .	A5
B.5	Save Data . . . . .	A6
<b>C</b>	<b>Appendix C</b>	<b>A7</b>
C.1	Quantile Regression . . . . .	A7
C.2	Descriptive Statistics . . . . .	A21
C.3	Daily plots: Code . . . . .	A24
C.4	Slope Estimates . . . . .	A27

## List of Tables

4.1	Descriptive Statistics for tsn-hrl . . . . .	15
4.2	Descriptive Statistics for cag-syy . . . . .	16
4.3	TSN:Quantile regression results . . . . .	17
4.4	HRL:Quantile regression results . . . . .	17
4.5	CAG:Quantile regression results . . . . .	18
4.6	SY Y:Quantile regression results . . . . .	18



## List of Figures

3.1	tsn logarithm of price and volume . . . . .	8
3.2	hrl logarithm of price and volume . . . . .	9
3.3	cag logarithm of price and volume . . . . .	10
3.4	syy logarithm of price and volume . . . . .	11
4.1	Tsn:slope estimates for dlnclose>0 . . . . .	19
4.2	Tsn:slope estimates for dlnclose<0 . . . . .	20
4.3	Hrl:slope estimates for dlnclose>0 . . . . .	20
4.4	Hrl:slope estimates for dlnclose<0 . . . . .	21
4.5	Cag:slope estimates for dlnclose>0 . . . . .	21
4.6	Cag:slope estimates for dlnclose<0 . . . . .	22
4.7	Syy:slope estimates for dlnclose>0 . . . . .	22
4.8	Syy:slope estimates for dlnclose<0 . . . . .	23





## 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*



## 1.1 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.

## 2.1 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.

## 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.

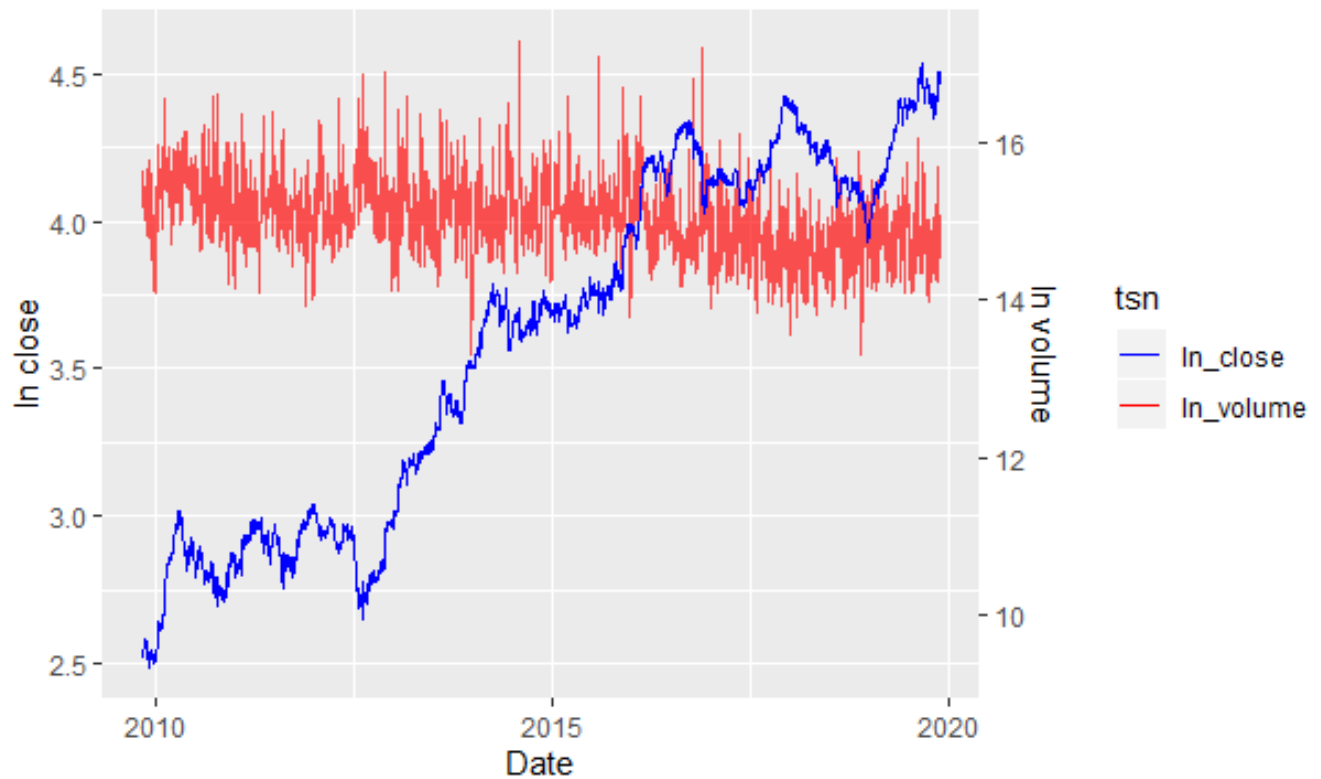


Figure 3.1: tsn logarithm of price and volume

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 SYE 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 SYE (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.



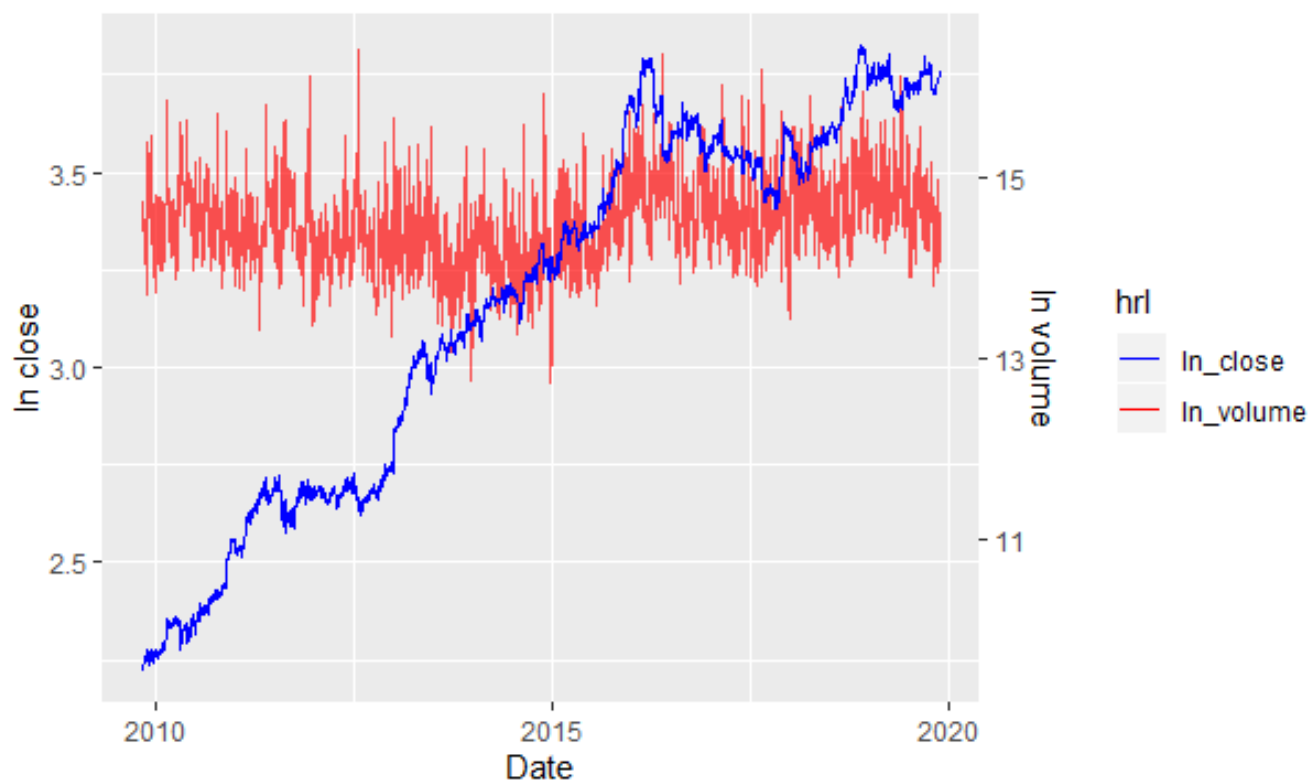


Figure 3.2: hrl logarithm of price and volume

### 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-

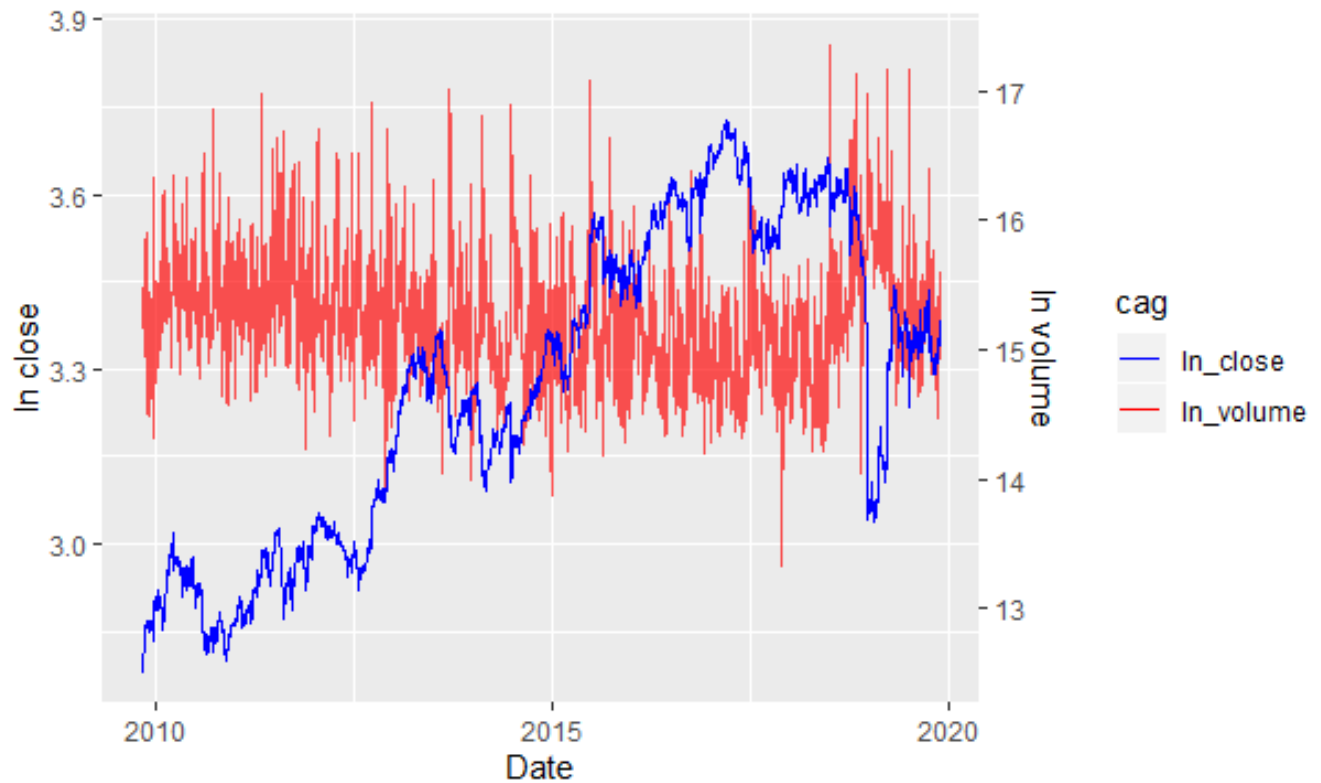


Figure 3.3: cag logarithm of price and volume

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 Ruder 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.

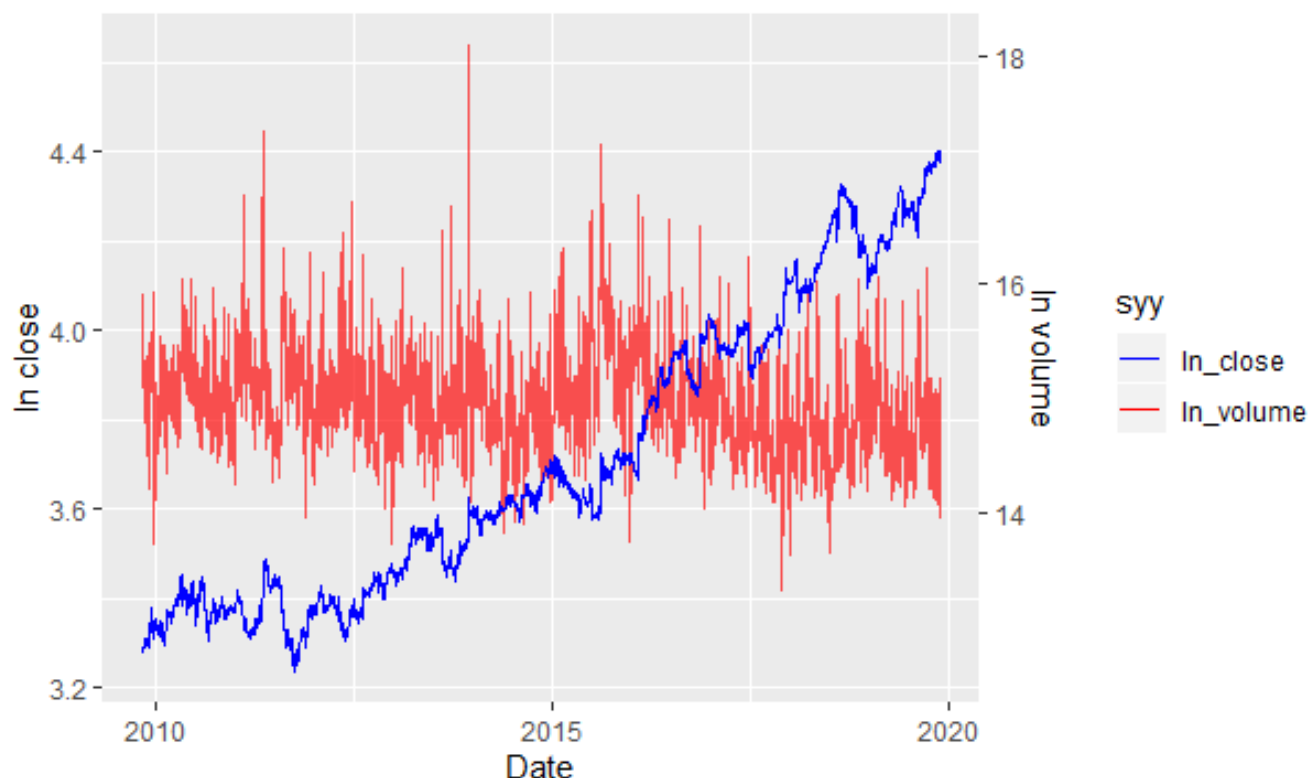


Figure 3.4: syy logarithm of price and volume

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 their 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 ana-

lyst 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:

$$F_Y(y) = P(Y \leq y) \quad (3.1)$$

The  $\tau$ th quantile of  $Y$  is given by:

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

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

Define the loss function as:

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

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

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

This can be shown by setting the derivative of the expected loss function to 0 and letting  $q_\tau$  be the solution of

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

This equation reduces to

$$0 = F_Y(q_\tau) - \tau, \quad (3.6)$$

and then to

$$F_Y(q_\tau) = \tau. \quad (3.7)$$

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

Consider  $\tau = 0.5$  and let  $q$  be an initial guess for  $q_\tau$ . 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

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

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.

## 4.1 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 Corporation and Conagra Brands) without an exception. In both cases, it is noticed a strong 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: SY: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

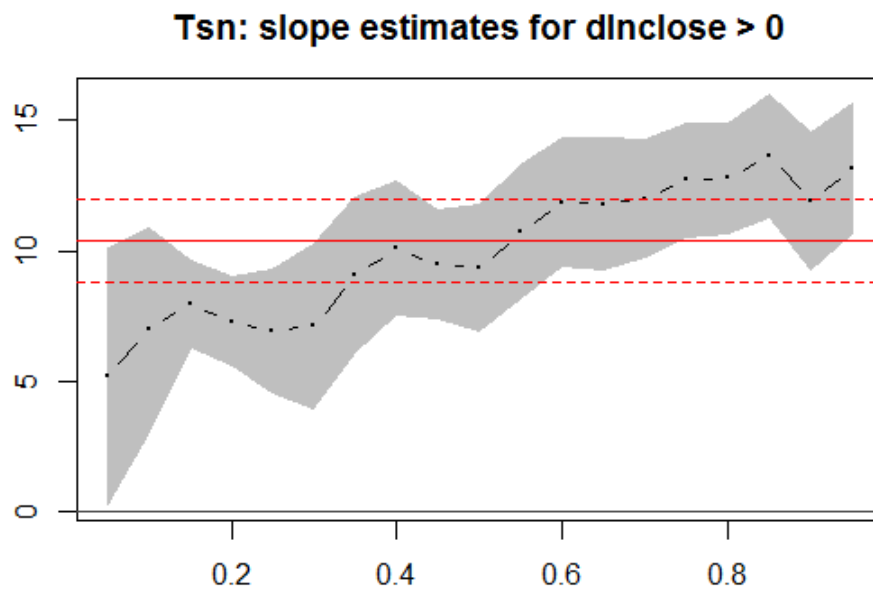


Figure 4.1: Tsn:slope estimates for dlnclose>0

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

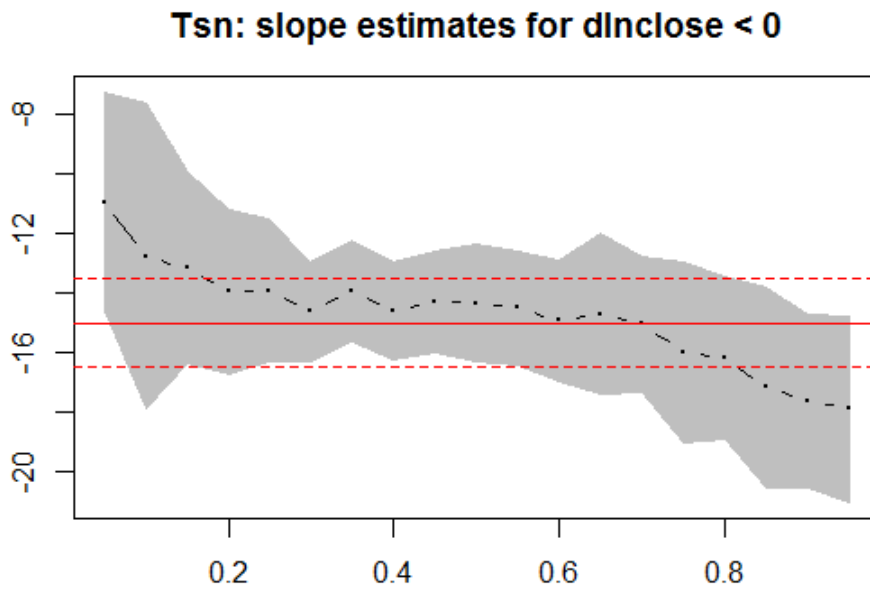


Figure 4.2: Tsn:slope estimates for dlnclose&lt;0

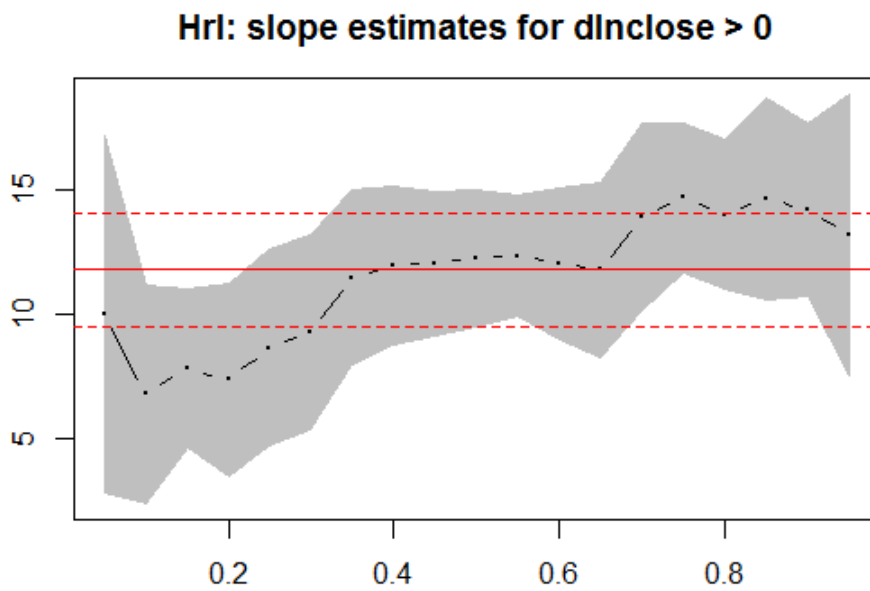


Figure 4.3: Hrl:slope estimates for dlnclose&gt;0

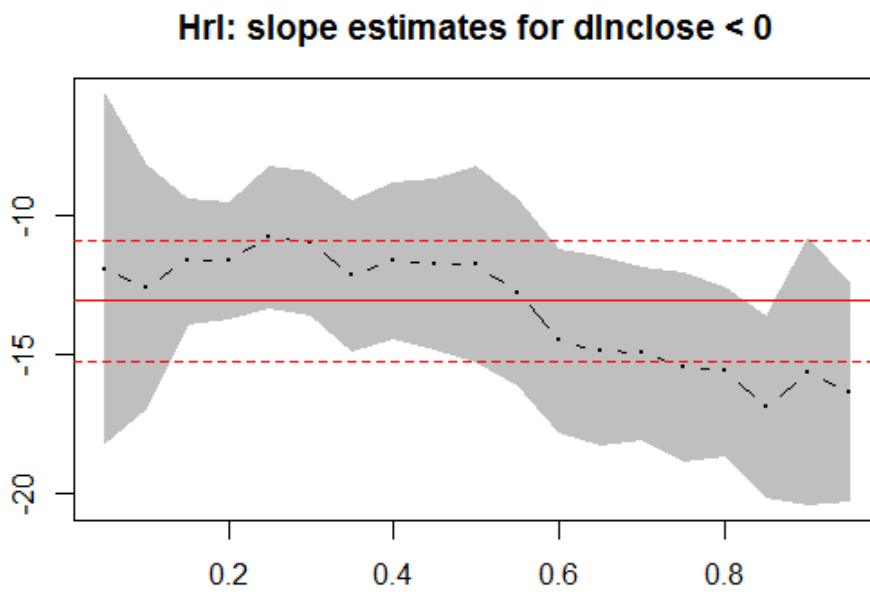


Figure 4.4: Hrl:slope estimates for dlnclose&lt;0

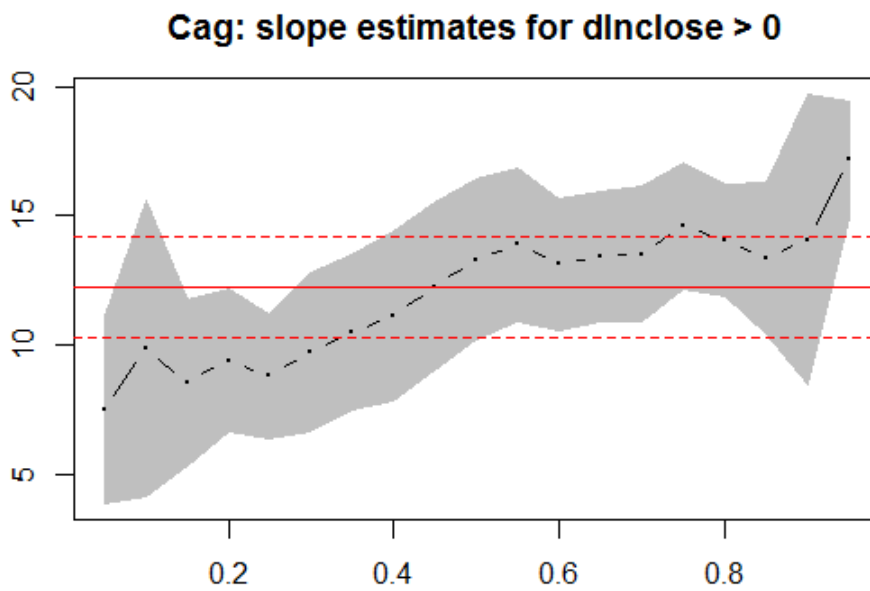
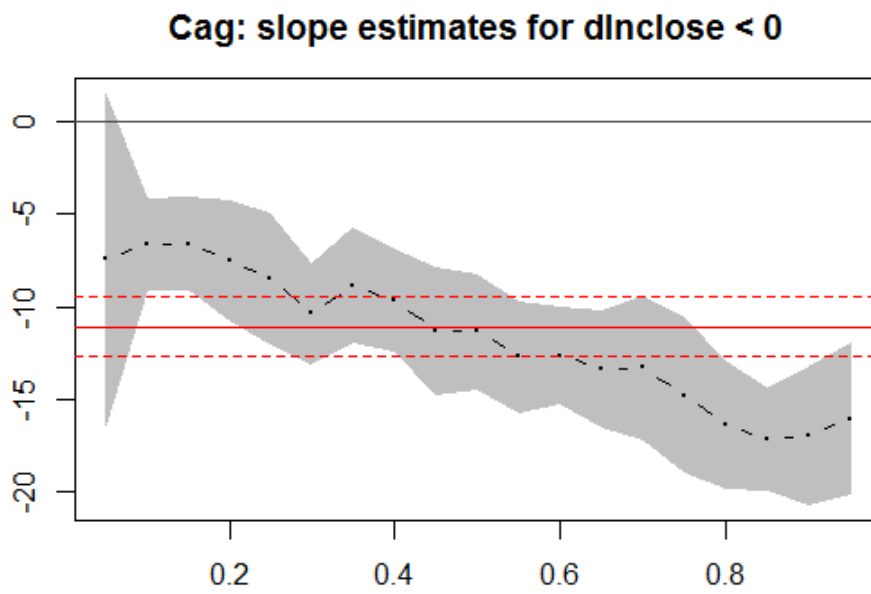
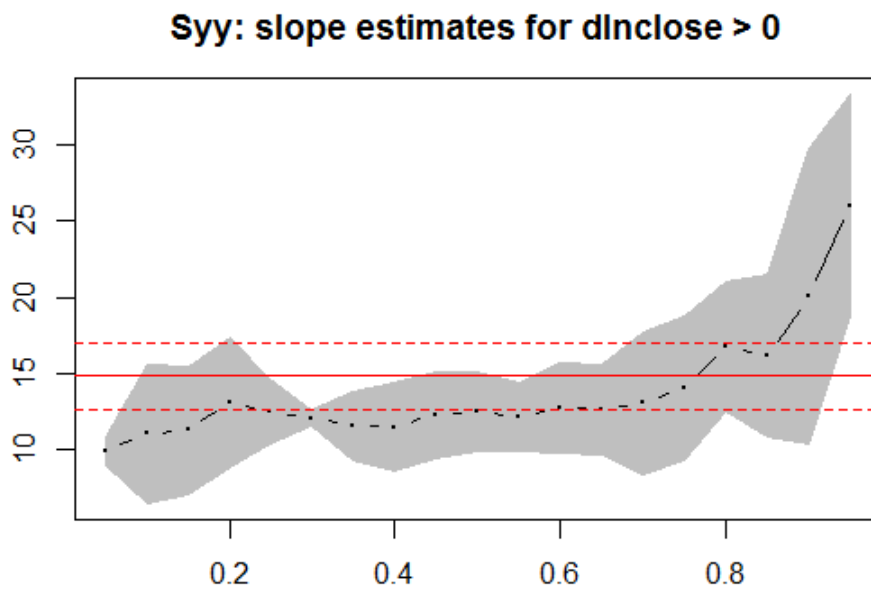


Figure 4.5: Cag:slope estimates for dlnclose&gt;0

Figure 4.6: Cag:slope estimates for  $dln\text{close}<0$ Figure 4.7: Syy:slope estimates for  $dln\text{close}>0$

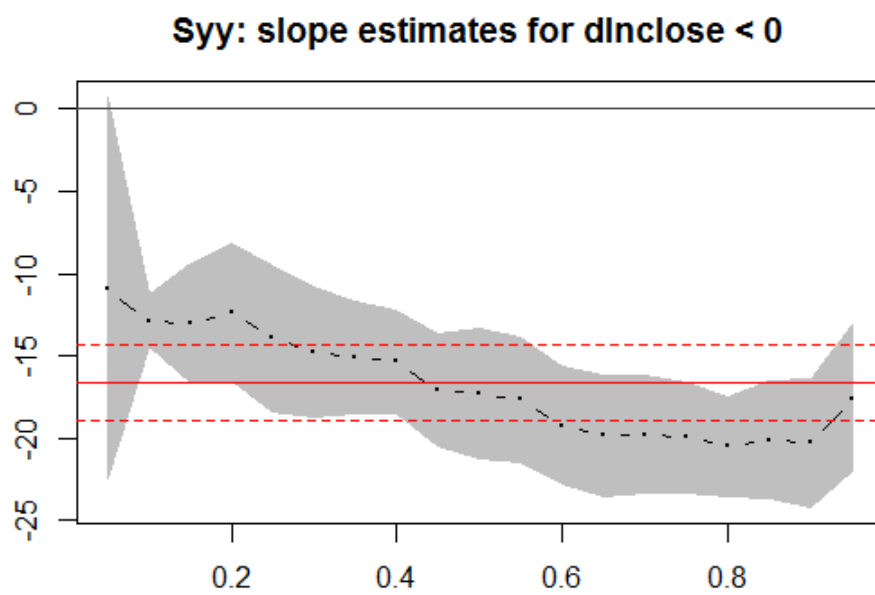


Figure 4.8: Syy:slope estimates for dlnclose&lt;0





## 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)

## 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

```
1 install.packages('tidyverse', dep = TRUE)
2 install.packages('tidyquant', dep = TRUE)
3 install.packages('fredr', dep = TRUE)
4 install.packages('quantl', dep = TRUE)
5 install.packages('ggthemes', dep = TRUE)
6 install.packages('ggplot2', dep = TRUE)
7 install.packages('ggrepel', dep = TRUE)
8 install.packages('readr', dep = TRUE)
9 install.packages('tidyr', dep = TRUE)
10 install.packages('lubridate', dep = TRUE)
11 install.packages('DT', dep = TRUE)
12 install.packages('scatterplot3d', dep = TRUE)
13 install.packages('Hmisc', dep = TRUE)
14 install.packages('pastecs', dep = TRUE)
15 install.packages('xtable', dep = TRUE)
```

## B.2 Installing R libraries

```
1 library(tidyverse, dep = TRUE)
2 library(tidyquant, dep = TRUE)
3 library(fredr, dep = TRUE)
4 library(Quandl, dep = TRUE)
5 library(ggthemes, dep = TRUE)
6 library(ggplot2, dep = TRUE)
7 library(ggrepel, dep = TRUE)
8 library(readr, dep = TRUE)
9 library(tidyr, dep = TRUE)
10 library(lubridate, dep = TRUE)
11 library(DT, dep = TRUE)
12 library(scatterplot3d, dep = TRUE)
13 library(Hmisc, dep = TRUE)
14 library(pastecs, dep = TRUE)
15 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:

```
1
2 Start_Date <- "2009-11-01"
3
4 hrl_d <- tq_get("HRL", from = Start_Date)
```

```
5 tsn_d <- tq_get("TSN", from = Start_Date)
6 cag_d <- tq_get("CAG", from = Start_Date)
7 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:

```
1 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:

```
1 cag_d <- cag_d %>%
2   mutate(dln_close = c(NA, diff(log(close))))
3 cag_d <- cag_d %>%
4   mutate(dln_volume = c(NA, diff(log(volume))))
5 cag_d2010 <- cag_d %>%
6   filter(date >= Start_Date2010)
7
8 tsn_d <- tsn_d %>%
9   mutate(dln_close = c(NA, diff(log(close))))
10 tsn_d <- tsn_d %>%
11   mutate(dln_volume = c(NA, diff(log(volume))))
12 tsn_d2010 <- tsn_d %>%
13   filter(date >= Start_Date2010)
14
15 syy_d <- syy_d %>%
```

```
16 mutate(dln_close = c(NA, diff(log(close))))
17 syy_d <- syy_d %>%
18   mutate(dln_volume = c(NA, diff(log(volume))))
19 syy_d2010 <- syy_d %>%
20   filter(date >= Start_Date2010)
21
22 hrl_d <- hrl_d %>%
23   mutate(dln_close = c(NA, diff(log(close))))
24 hrl_d <- hrl_d %>%
25   mutate(dln_volume = c(NA, diff(log(volume))))
26 hrl_d2010 <- hrl_d %>%
27   filter(date >= Start_Date2010)
```

## B.5 Save Data

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

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



## Appendix C

### C.1 Quantile Regression

```
1 taf=c(0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9)
2
3
4 for (i in 1:1){
5   ##### cag #####
6
7   j<-1
8
9   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010, dln_
10     close >0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
11   x<-as.data.frame(summary(RQ)$coefficients)
12   x$tau<-summary(RQ)$tau
13   x$explanation<-"cag_d2010 dln_close dln_volume & dln_close>0"
14   warn<-warnings()
15
16   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010, dln_
17     close <0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
18   x1<-as.data.frame(summary(RQ)$coefficients)
19   x1$tau<-summary(RQ)$tau
20   x1$explanation<-"cag_d2010 dln_close dln_volume & dln_close<0"
```

```

19 x<-rbind(x,x1)
20 warn<-c(warn,warnings())
21
22 RQ <- rq(dln_volume ~ dln_close, data=cag_d2010,tau = taf[j], method
    = "br", ci = TRUE, iid = TRUE)
23 x1<-as.data.frame(summary(RQ)$coefficients)
24 x1$tau<-summary(RQ)$tau
25 x1$explanation<-"cag_d2010 dln_close dln_volume"
26 x<-rbind(x,x1)
27 warn<-c(warn,warnings())
28
29
30 cag_dlnclose_control<-as.data.frame(x)
31
32
33
34 for (j in 2:9){
35   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010,
    dln_close > 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
36   x<-as.data.frame(summary(RQ)$coefficients)
37   x$tau<-summary(RQ)$tau
38   x$explanation<-"cag_d2010 dln_close dln_volume & dln_close > 0"
39   warn<-c(warn,warnings())
40
41   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010,
    dln_close < 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
42   x1<-as.data.frame(summary(RQ)$coefficients)
43   x1$tau<-summary(RQ)$tau
44   x1$explanation<-"cag_d2010 dln_close dln_volume & dln_close < 0"
45   x<-rbind(x,x1)
46   warn<-c(warn,warnings())
47
48   RQ <- rq(dln_volume ~ dln_close, data=cag_d2010,tau = taf[j],
    method = "br", ci = TRUE, iid = TRUE)

```

```

49   x1<-as.data.frame(summary(RQ)$coefficients)
50   x1$tau<-summary(RQ)$tau
51   x1$explanation<-"cag_d2010 dln_close dln_volume"
52   x<-rbind(x,x1)
53   warn<-c(warn,warnings())
54
55   cag_dlnclose_control<-rbind(cag_dlnclose_control,x)
56 }
57 warn<-c(warn,warnings())
58
59 j<-1
60
61 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010, dln_
   volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
62 x<-as.data.frame(summary(RQ)$coefficients)
63 x$tau<-summary(RQ)$tau
64 x$explanation<-"cag_d2010 dln_volume dln_close & dln_volume>0"
65 warn<-c(warn,warnings())
66
67 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010, dln_
   volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
68 x1<-as.data.frame(summary(RQ)$coefficients)
69 x1$tau<-summary(RQ)$tau
70 x1$explanation<-"cag_d2010 dln_volume dln_close & dln_volume<0"
71 x<-rbind(x,x1)
72 warn<-c(warn,warnings())
73
74 RQ <- rq(dln_volume ~ dln_close, data=cag_d2010,tau = taf[j], method
   = "br", ci = TRUE, iid = TRUE)
75 x1<-as.data.frame(summary(RQ)$coefficients)
76 x1$tau<-summary(RQ)$tau
77 x1$explanation<-"cag_d2010 dln_volume dln_close"
78 x<-rbind(x,x1)
79 warn<-c(warn,warnings())

```



```

80
81
82 cag_dlnvolume_control<-as.data.frame(x)
83
84
85 for (j in 2:9){
86   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010,
87     dln_volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
88   x<-as.data.frame(summary(RQ)$coefficients)
89   x$tau<-summary(RQ)$tau
90   x$explanation<-"cag_d2010 dln_volume dln_close & dln_volume>0"
91   warn<-c(warn, warnings())
92
93   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(cag_d2010,
94     dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
95   x1<-as.data.frame(summary(RQ)$coefficients)
96   x1$tau<-summary(RQ)$tau
97   x1$explanation<-"cag_d2010 dln_volume dln_close & dln_volume<0"
98   x<-rbind(x, x1)
99   warn<-c(warn, warnings())
100
101   RQ <- rq(dln_volume ~ dln_close, data=cag_d2010, tau = taf[j],
102     method = "br", ci = TRUE, iid = TRUE)
103   x1<-as.data.frame(summary(RQ)$coefficients)
104   x1$tau<-summary(RQ)$tau
105   x1$explanation<-"cag_d2010 dln_volume dln_close"
106   x<-rbind(x, x1)
107   warn<-c(warn, warnings())
108
109   cag_dlnvolume_control<-rbind(cag_dlnvolume_control, x)
110 }
111 warn<-c(warn, warnings())
112
113 ##### tsn #####

```

```

111
112   j<-1
113
114   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010, dln_
115     close >0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
116   x<-as.data.frame(summary(RQ)$coefficients)
117   x$tau<-summary(RQ)$tau
118   x$explanation<-"tsn_d2010 dln_close dln_volume & dln_close>0"
119   warn<-c(warn, warnings())
120
121   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010, dln_
122     close <0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
123   x1<-as.data.frame(summary(RQ)$coefficients)
124   x1$tau<-summary(RQ)$tau
125   x1$explanation<-"tsn_d2010 dln_close dln_volume & dln_close<0"
126   x<-rbind(x, x1)
127   warn<-c(warn, warnings())
128
129   RQ <- rq(dln_volume ~ dln_close, data=tsn_d2010, tau = taf[j], method
130     = "br", ci = TRUE, iid = TRUE)
131   x1<-as.data.frame(summary(RQ)$coefficients)
132   x1$tau<-summary(RQ)$tau
133   x1$explanation<-"tsn_d2010 dln_close dln_volume"
134   x<-rbind(x, x1)
135   warn<-c(warn, warnings())
136
137   tsn_dlnclose_control<-as.data.frame(x)
138
139   for (j in 2:9){
140     RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010,
141       dln_close >0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)

```

```

141 x<-as.data.frame(summary(RQ)$coefficients)
142 x$tau<-summary(RQ)$tau
143 x$explanation<-"tsn_d2010 dln_close dln_volume & dln_close>0"
144 warn<-c(warn, warnings())
145
146 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010,
dln_close < 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
147 x1<-as.data.frame(summary(RQ)$coefficients)
148 x1$tau<-summary(RQ)$tau
149 x1$explanation<-"tsn_d2010 dln_close dln_volume & dln_close<0"
150 x<-rbind(x, x1)
151 warn<-c(warn, warnings())
152
153 RQ <- rq(dln_volume ~ dln_close, data=tsn_d2010, tau = taf[j],
method = "br", ci = TRUE, iid = TRUE)
154 x1<-as.data.frame(summary(RQ)$coefficients)
155 x1$tau<-summary(RQ)$tau
156 x1$explanation<-"tsn_d2010 dln_close dln_volume"
157 x<-rbind(x, x1)
158 warn<-c(warn, warnings())
159
160 tsn_dln_close_control<-rbind(tsn_dln_close_control, x)
161 }
162 warn<-c(warn, warnings())
163
164 j<-1
165
166 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010, dln_
volume > 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
167 x<-as.data.frame(summary(RQ)$coefficients)
168 x$tau<-summary(RQ)$tau
169 x$explanation<-"tsn_d2010 dln_volume dln_close & dln_volume>0"
170 warn<-c(warn, warnings())
171

```

```
172 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010, dln_
    volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
173 x1<-as.data.frame(summary(RQ)$coefficients)
174 x1$tau<-summary(RQ)$tau
175 x1$explanation<-"tsn_d2010 dln_volume dln_close & dln_volume<0"
176 x<-rbind(x,x1)
177 warn<-c(warn, warnings())
178
179 RQ <- rq(dln_volume ~ dln_close, data=tsn_d2010,tau = taf[j], method
    = "br", ci = TRUE, iid = TRUE)
180 x1<-as.data.frame(summary(RQ)$coefficients)
181 x1$tau<-summary(RQ)$tau
182 x1$explanation<-"tsn_d2010 dln_volume dln_close"
183 x<-rbind(x,x1)
184 warn<-c(warn, warnings())
185
186
187 tsn_dlnvolume_control<-as.data.frame(x)
188
189
190 for (j in 2:9){
191   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010,
    dln_volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
192   x<-as.data.frame(summary(RQ)$coefficients)
193   x$tau<-summary(RQ)$tau
194   x$explanation<-"tsn_d2010 dln_volume dln_close & dln_volume>0"
195   warn<-c(warn, warnings())
196
197   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(tsn_d2010,
    dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
198   x1<-as.data.frame(summary(RQ)$coefficients)
199   x1$tau<-summary(RQ)$tau
200   x1$explanation<-"tsn_d2010 dln_volume dln_close & dln_volume<0"
201   x<-rbind(x,x1)
```

```

202   warn<-c(warn, warnings())
203
204   RQ <- rq(dln_volume ~ dln_close, data=tsn_d2010, tau = taf[j],
method = "br", ci = TRUE, iid = TRUE)
205   x1<-as.data.frame(summary(RQ)$coefficients)
206   x1$tau<-summary(RQ)$tau
207   x1$explanation<-"tsn_d2010 dln_volume dln_close"
208   x<-rbind(x, x1)
209   warn<-c(warn, warnings())
210
211   tsn_dlnvolume_control<-rbind(tsn_dlnvolume_control, x)
212 }
213 warn<-c(warn, warnings())
214
215 ##### hrl #####
216
217 j<-1
218
219 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010, dln_
close >0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
220 x<-as.data.frame(summary(RQ)$coefficients)
221 x$tau<-summary(RQ)$tau
222 x$explanation<-"hrl_d2010 dln_close dln_volume & dln_close>0"
223 warn<-c(warn, warnings())
224
225 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010, dln_
close <0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
226 x1<-as.data.frame(summary(RQ)$coefficients)
227 x1$tau<-summary(RQ)$tau
228 x1$explanation<-"hrl_d2010 dln_close dln_volume & dln_close<0"
229 x<-rbind(x, x1)
230 warn<-c(warn, warnings())
231

```

```
232 RQ <- rq(dln_volume ~ dln_close, data=hrl_d2010, tau = taf[j], method
    = "br", ci = TRUE, iid = TRUE)
233 x1<-as.data.frame(summary(RQ)$coefficients)
234 x1$tau<-summary(RQ)$tau
235 x1$explanation<-"hrl_d2010 dln_close dln_volume"
236 x<-rbind(x, x1)
237 warn<-c(warn, warnings())
238
239
240 hrl_dln_close_control<-as.data.frame(x)
241
242
243
244 for (j in 2:9){
245   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010,
    dln_close > 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
246   x<-as.data.frame(summary(RQ)$coefficients)
247   x$tau<-summary(RQ)$tau
248   x$explanation<-"hrl_d2010 dln_close dln_volume & dln_close > 0"
249   warn<-c(warn, warnings())
250
251   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010,
    dln_close < 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
252   x1<-as.data.frame(summary(RQ)$coefficients)
253   x1$tau<-summary(RQ)$tau
254   x1$explanation<-"hrl_d2010 dln_close dln_volume & dln_close < 0"
255   x<-rbind(x, x1)
256   warn<-c(warn, warnings())
257
258   RQ <- rq(dln_volume ~ dln_close, data=hrl_d2010, tau = taf[j],
    method = "br", ci = TRUE, iid = TRUE)
259   x1<-as.data.frame(summary(RQ)$coefficients)
260   x1$tau<-summary(RQ)$tau
261   x1$explanation<-"hrl_d2010 dln_close dln_volume"
```

```

262   x<-rbind(x,x1)
263   warn<-c(warn, warnings())
264
265   hrl_dlnclose_control<-rbind(hrl_dlnclose_control,x)
266 }
267 warn<-c(warn, warnings())
268
269 j<-1
270
271 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010, dln_
  volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
272 x<-as.data.frame(summary(RQ)$coefficients)
273 x$tau<-summary(RQ)$tau
274 x$explanation<-"hrl_d2010 dln_volume dln_close & dln_volume>0"
275 warn<-c(warn, warnings())
276
277 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010, dln_
  volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
278 x1<-as.data.frame(summary(RQ)$coefficients)
279 x1$tau<-summary(RQ)$tau
280 x1$explanation<-"hrl_d2010 dln_volume dln_close & dln_volume<0"
281 x<-rbind(x,x1)
282 warn<-c(warn, warnings())
283
284 RQ <- rq(dln_volume ~ dln_close, data=hrl_d2010,tau = taf[j], method
  = "br", ci = TRUE, iid = TRUE)
285 x1<-as.data.frame(summary(RQ)$coefficients)
286 x1$tau<-summary(RQ)$tau
287 x1$explanation<-"hrl_d2010 dln_volume dln_close"
288 x<-rbind(x,x1)
289 warn<-c(warn, warnings())
290
291
292 hrl_dlnvolume_control<-as.data.frame(x)

```

```

293
294
295 for (j in 2:9){
296   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010,
297     dln_volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
298   x<-as.data.frame(summary(RQ)$coefficients)
299   x$tau<-summary(RQ)$tau
300   x$explanation<-"hrl_d2010 dln_volume dln_close & dln_volume>0"
301   warn<-c(warn, warnings())
302
303   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(hrl_d2010,
304     dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
305   x1<-as.data.frame(summary(RQ)$coefficients)
306   x1$tau<-summary(RQ)$tau
307   x1$explanation<-"hrl_d2010 dln_volume dln_close & dln_volume<0"
308   x<-rbind(x, x1)
309   warn<-c(warn, warnings())
310
311   RQ <- rq(dln_volume ~ dln_close, data=hrl_d2010, tau = taf[j],
312     method = "br", ci = TRUE, iid = TRUE)
313   x1<-as.data.frame(summary(RQ)$coefficients)
314   x1$tau<-summary(RQ)$tau
315   x1$explanation<-"hrl_d2010 dln_volume dln_close"
316   x<-rbind(x, x1)
317   warn<-c(warn, warnings())
318
319   hrl_dlnvolume_control<-rbind(hrl_dlnvolume_control, x)
320 }
321 warn<-c(warn, warnings())
322 ##### syy #####
323
j<-1

```



```

324 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010, dln_
      close > 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
325 x <- as.data.frame(summary(RQ)$coefficients)
326 x$tau <- summary(RQ)$tau
327 x$explanation <- "syy_d2010 dln_close dln_volume & dln_close > 0"
328 warn <- c(warn, warnings())
329
330 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010, dln_
      close < 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
331 x1 <- as.data.frame(summary(RQ)$coefficients)
332 x1$tau <- summary(RQ)$tau
333 x1$explanation <- "syy_d2010 dln_close dln_volume & dln_close < 0"
334 x <- rbind(x, x1)
335 warn <- c(warn, warnings())
336
337 RQ <- rq(dln_volume ~ dln_close, data = syy_d2010, tau = taf[j], method
      = "br", ci = TRUE, iid = TRUE)
338 x1 <- as.data.frame(summary(RQ)$coefficients)
339 x1$tau <- summary(RQ)$tau
340 x1$explanation <- "syy_d2010 dln_close dln_volume"
341 x <- rbind(x, x1)
342 warn <- c(warn, warnings())
343
344
345 syy_dln_close_control <- as.data.frame(x)
346
347
348
349 for (j in 2:9){
350   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010,
      dln_close > 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
351   x <- as.data.frame(summary(RQ)$coefficients)
352   x$tau <- summary(RQ)$tau
353   x$explanation <- "syy_d2010 dln_close dln_volume & dln_close > 0"

```

```

354   warn<-c(warn, warnings())
355
356   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010,
357   dln_close < 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
358   x1<-as.data.frame(summary(RQ)$coefficients)
359   x1$tau<-summary(RQ)$tau
360   x1$explanation<-"syy_d2010 dln_close dln_volume & dln_close < 0"
361   x<-rbind(x, x1)
362   warn<-c(warn, warnings())
363
364   RQ <- rq(dln_volume ~ dln_close, data=syy_d2010, tau = taf[j],
365   method = "br", ci = TRUE, iid = TRUE)
366   x1<-as.data.frame(summary(RQ)$coefficients)
367   x1$tau<-summary(RQ)$tau
368   x1$explanation<-"syy_d2010 dln_close dln_volume"
369   x<-rbind(x, x1)
370   warn<-c(warn, warnings())
371
372   syy_dln_close_control<-rbind(syy_dln_close_control, x)
373 }
374 warn<-c(warn, warnings())
375
376 j<-1
377
378 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010, dln_
379 volume > 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
380 x<-as.data.frame(summary(RQ)$coefficients)
381 x$tau<-summary(RQ)$tau
382 x$explanation<-"syy_d2010 dln_volume dln_close & dln_volume > 0"
383 warn<-c(warn, warnings())
384
385 RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010, dln_
386 volume < 0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
387 x1<-as.data.frame(summary(RQ)$coefficients)

```

```

384 x1$tau<-summary(RQ)$tau
385 x1$explanation<-"syy_d2010 dln_volume dln_close & dln_volume<0"
386 x<-rbind(x,x1)
387 warn<-c(warn,warnings())
388
389 RQ <- rq(dln_volume ~ dln_close, data=syy_d2010, tau = taf[j], method
= "br", ci = TRUE, iid = TRUE)
390 x1<-as.data.frame(summary(RQ)$coefficients)
391 x1$tau<-summary(RQ)$tau
392 x1$explanation<-"syy_d2010 dln_volume dln_close"
393 x<-rbind(x,x1)
394 warn<-c(warn,warnings())
395
396
397 syy_dlnvolume_control<-as.data.frame(x)
398
399
400 for (j in 2:9){
401   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010,
dln_volume>0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
402   x<-as.data.frame(summary(RQ)$coefficients)
403   x$tau<-summary(RQ)$tau
404   x$explanation<-"syy_d2010 dln_volume dln_close & dln_volume>0"
405   warn<-c(warn,warnings())
406
407   RQ <- rq(dln_volume ~ dln_close, data = dplyr::filter(syy_d2010,
dln_volume<0), tau = taf[j], method = "br", ci = TRUE, iid = TRUE)
408   x1<-as.data.frame(summary(RQ)$coefficients)
409   x1$tau<-summary(RQ)$tau
410   x1$explanation<-"syy_d2010 dln_volume dln_close & dln_volume<0"
411   x<-rbind(x,x1)
412   warn<-c(warn,warnings())
413

```

```

414   RQ <- rq(dln_volume ~ dln_close, data=syy_d2010, tau = taf[j],
method = "br", ci = TRUE, iid = TRUE)
415   x1<-as.data.frame(summary(RQ)$coefficients)
416   x1$tau<-summary(RQ)$tau
417   x1$explanation<-"syy_d2010 dln_volume dln_close"
418   x<-rbind(x, x1)
419   warn<-c(warn, warnings())
420
421   syy_dlnvolume_control<-rbind(syy_dlnvolume_control, x)
422 }
423 warn<-c(warn, warnings())

```

## C.2 Descriptive Statistics

Useful libraries:

```

1 library(moments)
2 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:

```

1 ## Descriptive Statistics per firm
2
3 TSN_d.Y <- diff("tsn_d2010")
4 describe(tsn_d2010)
5 x<- describe(tsn_d2010)
6 x<-x[8:9,]
7 x = subset(x, select = -c(vars, n, trimmed, range, mad) )
8 t_x <- transpose(x)

```

```
9 colnames(t_x) <- rownames(x)
10 rownames(t_x) <- colnames(x)
11 xtable_tsn<-xtable(t_x)
12 #isna<-table(is.na(x))
13 warn<-c(warn, warnings())
14
15 t_table<-as.data.frame(t_x)
16
17 HRL_d.Y <- diff("hrl_d2010")
18 describe(hrl_d2010)
19 x<- describe(hrl_d2010)
20 x<-x[8:9,]
21 x = subset(x, select = -c(vars,n,trimmed,range,mad) )
22 t_x <- transpose(x)
23 colnames(t_x) <- rownames(x)
24 rownames(t_x) <- colnames(x)
25 xtable_hrl<-xtable(t_x)
26 #isna<-table(is.na(x))
27 warn<-c(warn, warnings())
28
29 t_table<-cbind(t_table, t_x)
30
31 CAG_d.Y <- diff("cag_d2010")
32 describe(cag_d2010)
33 x<- describe(cag_d2010)
34 x<-x[8:9,]
35 x = subset(x, select = -c(vars,n,trimmed,range,mad) )
36 t_x <- transpose(x)
37 colnames(t_x) <- rownames(x)
38 rownames(t_x) <- colnames(x)
39 xtable_cag<-xtable(t_x)
40 #isna<-table(is.na(x))
41 warn<-c(warn, warnings())
42
```

```
43 t_table<-cbind(t_table , t_x)
44
45 SYY_d.Y <- diff("syy_d2010")
46 describe(syy_d2010)
47 x<- describe(syy_d2010)
48 x<-x[8:9 ,]
49 x = subset(x, select = -c(vars , n, trimmed , range , mad) )
50 t_x <- transpose(x)
51 colnames(t_x) <- rownames(x)
52 rownames(t_x) <- colnames(x)
53 xtable_syy<-xtable(t_x)
54 #isna<-table(is.na(x))
55 warn<-c(warn , warnings())
56
57 t_table<-cbind(t_table , t_x)
```

```
1 ## Tests
2
3 ##https://cran.r-project.org/web/packages/moments/moments.pdf
4 library(moments)
5 library(normtest)
6
7
8 dlnp<-cag_d2010$dln_close
9 skewness(dlnp)
10 ### skewness
11 agostino.test(dlnp, alternative = c("two.sided", "less", "greater"))
12
13 ### normality
14 jarque.test(dlnp)
15
16 #kurtosis
17 kurtosis(dlnp, na.rm = FALSE)
```

```

18 moment(dlnp, order = 1, central = FALSE, absolute = FALSE, na.rm =
    FALSE)
19
20 ##https://www.rdocumentation.org/packages/normtest/versions/1.1/topics/
    kurtosis.norm.test
21 kurtosis.norm.test(dlnp, nrepl=2000)

```

### C.3 Daily plots: Code

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

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

```
1 library(plotly)
2 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:

```

1 library(SciViews)
2
3 ## daily logarithm close price and volume
4 ### TSN
5 dftogether<-data.frame(tsn_d$date,tsn_d$close,tsn_d$volume)
6 dftogether$ln_close<-ln(dftogether$tsn_d.close)
7 dftogether$ln_volume<-ln(dftogether$tsn_d.volume)
8
9 p <- ggplot(dftogether, aes(x = dftogether$tsn_d.date))

```

```

10 p <- p + geom_line(aes(y = ln_volume/3.9, colour = "ln_volume"), alpha=1
    /1.5)
11 p <- p + geom_line(aes(y = ln_close, colour = "ln_close"))
12 p <- p + scale_y_continuous(sec.axis = sec_axis(~.*3.9, name = "ln
    volume"))
13 p <- p + scale_colour_manual(values = c("blue", "red"))
14 p <- p + labs(y = "ln close",
15             x = "Date",
16             colour = "tsn")
17 ##p <- p + theme(legend.position = c(0.8, 0.9))
18 p
19
20 ###          HRL
21 dftogether<-data.frame(hrl_d$date, hrl_d$close, hrl_d$volume)
22 dftogether$ln_close<-ln(dftogether$hrl_d.close)
23 dftogether$ln_volume<-ln(dftogether$hrl_d.volume)
24
25 p <- ggplot(dftogether, aes(x = dftogether$hrl_d.date))
26 p <- p + geom_line(aes(y = ln_volume/4.5, colour = "ln_volume"), alpha=1
    /1.5)
27 p <- p + geom_line(aes(y = ln_close, colour = "ln_close"))
28 p <- p + scale_y_continuous(sec.axis = sec_axis(~.*4.5, name = "ln
    volume"))
29 p <- p + scale_colour_manual(values = c("blue", "red"))
30 p <- p + labs(y = "ln close",
31             x = "Date",
32             colour = "hrl")
33 ##p <- p + theme(legend.position = c(0.8, 0.9))
34 p
35
36 ###          CAG
37
38 dftogether<-data.frame(cag_d$date, cag_d$close, cag_d$volume)
39 dftogether$ln_close<-ln(dftogether$cag_d.close)

```



```

40 dftogether$ln_volume<-ln(dftogether$cag_d.volume)
41
42 p <- ggplot(dftogether , aes(x = dftogether$cag_d.date))
43 p <- p + geom_line(aes(y = ln_volume/4.5, colour = "ln_volume"),alpha=1
    /1.5)
44 p <- p + geom_line(aes(y = ln_close , colour = "ln_close"))
45 p <- p + scale_y_continuous(sec.axis = sec_axis(~.*4.5, name = "ln
    volume"))
46 p <- p + scale_colour_manual(values = c("blue", "red"))
47 p <- p + labs(y = "ln close",
48             x = "Date",
49             colour = "cag")
50 ##p <- p + theme(legend.position = c(0.8, 0.9))
51 p
52
53
54 ###          SYR
55 dftogether<-data.frame(syy_d$date ,syy_d$close ,syy_d$volume)
56 dftogether$ln_close<-ln(dftogether$syy_d.close)
57 dftogether$ln_volume<-ln(dftogether$syy_d.volume)
58
59 p <- ggplot(dftogether , aes(x = dftogether$syy_d.date))
60 p <- p + geom_line(aes(y = ln_volume/3.9, colour = "ln_volume"),alpha=1
    /1.5)
61 p <- p + geom_line(aes(y = ln_close , colour = "ln_close"))
62 p <- p + scale_y_continuous(sec.axis = sec_axis(~.*3.9, name = "ln
    volume"))
63 p <- p + scale_colour_manual(values = c("blue", "red"))
64 p <- p + labs(y = "ln close",
65             x = "Date",
66             colour = "syy")
67 ##p <- p + theme(legend.position = c(0.8, 0.9))
68 p

```

## C.4 Slope Estimates

```
1 ##Plots
2 ##                               TSN
3 mydata<-tsn_d2010
4 keeps<-c("date","dln_volume","dln_close")
5 mydata<-mydata[keeps]
6 names(mydata)<-c("date","Y","X")
7
8
9 ##### Plotting data_Positive
10  quantreg.all.pos <- rq(Y ~ X, data=filter(mydata, X>0), tau = seq
11    (0.05, 0.95, by = 0.05))
12  quantreg.plot.pos <- summary(quantreg.all.pos)
13  plot(quantreg.plot.pos, parm=2, main="tsn: slope estimates for
14    dlnclose > 0")
15
16 ##### Plotting data_Negative
17  quantreg.all.neg <- rq(Y ~ X, data=filter(mydata, X<0), tau = seq
18    (0.05, 0.95, by = 0.05))
19  quantreg.plot.neg <- summary(quantreg.all.neg)
20  plot(quantreg.plot.neg, parm=2, main="tsn: slope estimates for
21    dlnclose < 0")
22
23 ##                               HRL
24 mydata<-hrl_d2010
25 keeps<-c("date","dln_volume","dln_close")
26 mydata<-mydata[keeps]
27 names(mydata)<-c("date","Y","X")
28
29 ##### Plotting data_Positive
```

```

27 quantreg.all.pos <- rq(Y ~ X, data=filter(mydata, X>0), tau = seq
    (0.05, 0.95, by = 0.05))
28 quantreg.plot.pos <- summary(quantreg.all.pos)
29 plot(quantreg.plot.pos, parm=2, main="hrl: slope estimates for
    dlnclose > 0")
30
31 ##### Plotting data_Negative
32 quantreg.all.neg <- rq(Y ~ X, data=filter(mydata, X<0), tau = seq
    (0.05, 0.95, by = 0.05))
33 quantreg.plot.neg <- summary(quantreg.all.neg)
34 plot(quantreg.plot.neg, parm=2, main="hrl: slope estimates for
    dlnclose < 0")
35
36
37 ## CAG
38 mydata<-cag_d2010
39 keeps<-c("date", "dln_volume", "dln_close")
40 mydata<-mydata[keeps]
41 names(mydata)<-c("date", "Y", "X")
42
43
44 ##### Plotting data_Positive
45 quantreg.all.pos <- rq(Y ~ X, data=filter(mydata, X>0), tau = seq
    (0.05, 0.95, by = 0.05))
46 quantreg.plot.pos <- summary(quantreg.all.pos)
47 plot(quantreg.plot.pos, parm=2, main="cag: slope estimates for
    dlnclose > 0")
48
49 ##### Plotting data_Negative
50 quantreg.all.neg <- rq(Y ~ X, data=filter(mydata, X<0), tau = seq
    (0.05, 0.95, by = 0.05))
51 quantreg.plot.neg <- summary(quantreg.all.neg)
52 plot(quantreg.plot.neg, parm=2, main="cag: slope estimates for
    dlnclose < 0")

```

```
53
54
55 ##                               SYY
56 mydata<-syy_d2010
57 keeps<-c("date", "dln_volume", "dln_close")
58 mydata<-mydata[keeps]
59 names(mydata)<-c("date", "Y", "X")
60
61
62 ##### Plotting data_Positive
63 quantreg.all.pos <- rq(Y ~ X, data=filter(mydata, X>0), tau = seq
64   (0.05, 0.95, by = 0.05))
65 quantreg.plot.pos <- summary(quantreg.all.pos)
66 plot(quantreg.plot.pos, parm=2, main="syy: slope estimates for
67   dln_close > 0")
68
69 ##### Plotting data_Negative
70 quantreg.all.neg <- rq(Y ~ X, data=filter(mydata, X<0), tau = seq
71   (0.05, 0.95, by = 0.05))
72 quantreg.plot.neg <- summary(quantreg.all.neg)
73 plot(quantreg.plot.neg, parm=2, main="syy: slope estimates for
74   dln_close < 0")
```