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Msc Economics & Business
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The Effect of Mood on Stock Returns

A comparison between Netherlands and Italy

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Abstract

Empirical findings in finance and experimental evidence from psychology suggest that emotions significantly influence human decision-making. The sentiments of investors have been proved to affect stock market returns. Experimental evidence in psychology suggests that the weather has an impact on agents' mood, which could, in turn, creates repercussion in financial markets. The purpose of this study is to examine whether meteorological conditions affect stock returns and if the results are valid for different countries. In particular, two distinct countries, namely Italy and the Netherlands, are analysed.

The hypothesis is supported by previous studies such as Saunders (1993) and Hirshleifer and Shumway (2003). However, the results of this study differ from previous researches. The main finding is that the Wind Speed strongly influences the returns of the stock market index during the opening hours, and the other weather variables are not significant after controlling for this factor.

Acknowledgment

I would like to express my sincere thank to the Dutch firm MeteoGroup, and in particular to Robert Mureau for providing the data used in the analysis. I would not have achieved these results, and this thesis would not have been completed without the help that I have received from him.

Mirko Federico Ravasi

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1 Introduction

Empirical findings in finance and experimental evidence from psychology suggest that emotions significantly influence human decision-making. Previous empirical studies illustrate the existence of a relationship between investors' moods and stock returns. Specifically, Saunders (1993) and Hirshleifer and Shumway (2003) have indicated that weather conditions correlate with stock returns.

The main question examined in this paper is whether a relationship between weather conditions and stock returns exists in the Dutch and Italian stock markets. Furthermore, another objective of this study is to examine whether factors that influence the Amsterdam stock exchange also impact the Italian stock exchange. Italy has notoriously fewer adverse meteorological conditions than the Netherlands, and for this reason, the mood of investors located in the Netherlands should be less influenced by adverse weather than the mood of investors located in Italy. However, Italy has a wider territory and a more heterogeneous population than the Netherlands, which could result in a more mixed effect of the weather variables on the mood of investors.

In the current research, a regression analysis with specification and heteroskedasticity tests is performed. To solve the problem caused by the presence of heteroskedasticity, the standard errors of the estimated coefficients are clustered on the variable month. Moreover, the robustness test is performed through the use of a generalised autoregressive heteroskedasticity consistent model. The main findings of the current research suggest that investors located in the Netherlands allow their moods to be influenced by wind speed. However, when considering the Italian data, no particular effect is observed, which could be the result of the aforementioned heterogeneity of the Italian population in conjunction with the collection of the data belonging only from the Milan area.

2 Literature Review

2.1 Traditional Finance

Fama (1970) has reviewed the assumptions behind the idea of efficient capital markets. A capital market is an instrument that investors can use to allocate resources, make investments, and trade securities. A main concern of financial academics is whether a firm's stock price reflects its real value. In this regard, Fama (1970) recalls the hypotheses of efficient capital markets in their three forms: weak, semi-strong, and strong. In the weak form, security prices incorporate information from historical prices. In the semi-strong form, security prices adjust themselves also regarding relevant economical information. In the strong form, security prices adjust themselves also taking into consideration the fact that only some groups of investors have access to relevant information. However, Fama (1970) asserts that the descriptive validity of these forms of efficiency must be tested empirically, and data does not always support them.

Fama, Shiller, and Hansen (Committee & others 2013) examined the fundamental problem regarding the correctness of asset prices. Fama (Committee & others 2013) has explained that to test whether prices correctly incorporate all relevant available information so that deviations from expected returns cannot be predicted, researchers need to know what these expected returns are. The strong evidence emerging from the study by Fama, Shiller, and Hansen is the challenge of predicting asset prices over short time horizons. However, they also have asserted that forecasting trends in asset prices over the long term is possible (Committee & others 2013). Another interesting point made in this study is the importance assigned to behavioural finance approaches as instruments for explaining deviations from expected returns.

Shiller, Fischer, and Friedman (1984) have argued against the assumption of investors' rationality. Firstly, arguing that the impossibility of predicting asset prices, which is the foundation of the most robust criticism on the role of mass psychology in financial markets, is not a reason to exclude the presence of irrational investors operating in the market. Shiller, Fischer, and Friedman (1984) suggest that rational agents could spend most of their free time discussing about investment opportunities, this would reflect in the creation of social movement, and consequently impact asset prices. Additionally, following the psychology literature, Shiller asserted that investors are subject to behavioural biases in the decision-making process, including, but not limited to, overreaction, group thinking, overconfidence, and self-attribution bias.

2.2 Sentiment and Stock Returns

Building on Shiller's work, Subrahmanyam (2008) reviewed and summarised the academic literature concerning the fields of traditional and behavioural finance, stressing that the latter field can explain certain results that the former cannot. However, Subrahmanyam (2008) also takes into consideration the objections made to behavioural finance approaches. First, due to the extensive empirical observations used to support behavioural finance models, the study argued that when a certain pattern is identified, a fitting model is introduced accordingly. Secondly, it is argued that an extensive use of data mining is employed to find these patterns. While it is important to acknowledge criticisms of behavioural finance, some authors have found strong support for the irrationality of investors and, in particular, the existence of a relationship between investors' moods and stock returns.

Saunders (1993) found that stock return movements cannot be entirely explained by traditional finance theory even after accounting for market imperfections and considering the economic information acquired by agents and financial markets. Saunder's (1993) study illustrates the importance of including behavioural factors in financial models and the role of investor psychology in determining stock prices. This study examined the relationship between weather conditions in New York City and movements in its stock exchange and found that factors like the weather conditions besides pure economic information regularly influence stock returns.

Similar to Saunders's work, Hirshleifer and Shumway (2003) considered the relationship between early morning sunshine and the market index stock returns on the same day for 26 different international stock exchanges between 1982 and 1997. Their findings suggest a strong and significant correlation between sunshine and stock returns. Moreover, sunshine was the weather variable that had the greatest impact, as rain and snow were unrelated to returns after sunshine was controlled for. Hirshleifer and Shumway's (2003) research suggests that investors' moods and, in turn, their decisions are affected by the weather. As a result, the stock exchange is also affected by the weather. Chang, Nieh, and Yang (2006) studied investors' behaviour in relation to weather changes in Taiwan. The findings of the study identify cloudiness and temperature as two important factors that affect stock returns. Moreover, the researchers employed a generalised autoregressive conditional heteroskedasticity (GARCH) model to account for variations in volatility over time. The employment of this model is relevant as it includes in the analysis the time-varying volatility feature, which is not taken into account in linear models. Yoon and Kang (2009) applied the same process used in the aforementioned by Chang, Nieh, and Yang (2006) to the Korean market. However, their findings were mixed. While they found a strong and significant weather effect during periods of crisis, the effect weakened after those periods, which is explained as a probable "result of the abolition of restrictions on foreign investors and the development of electronic trading systems in the Korean stock market".

Yuan, Zheng, and Zhu (2006) investigated another factor that influences stock returns, which cannot be explained through the hypotheses of rationality. They studied the relationship between lunar phases and stock market returns in several countries. Their findings confirm that stock returns are lower around the full moon than the new moon. This effect was still significant after accounting for macroeconomic announcements and global shocks. Interestingly, as Yuan, Zheng, and Zhu (2006) asserted, the psychology literature stresses a link between lunar phases and people's moods.

Extensive literature illustrates the relationship between weather conditions and stock returns. Nevertheless, the results of a study by Goetzmann and Zhu (2005), in which the stock markets of five major US cities were analysed, suggest that weather factors do not affect returns. On the other hand, Goetzmann and Zhu (2005) recommend focusing on market makers located in the city where the exchange is located rather than considering individual investors. This procedure could improve the accuracy of this study and in particular when considering investors located in Milan.

2.3 Mood and Risk Attitude

The interaction between mood and risk attitudes may explain the existence of the relationship between weather conditions and stock returns. Cahit, Guven, and Hoxa (2015) hypothesized that sunshine is a predictor of happiness and, consequently, related it to risk attitudes. They found that happier people are generally more risk averse. Moreover, in examining financial decisions, they found that happier people choose safer investments and have longer time horizons. Lepori's (2015) findings also support the hypothesis that happier people are more risk averse. When examining the relationship between people's attendance at comedy events on the weekend and stock returns the following Monday, Cahit, Guven, and Hoxha (2015) found an inverse correlation between these two variables. This result confirms Lepori's (2015) results. These two studies provide insights that require further consideration. An association exists between risk attitudes and mood. Additionally, investors' risk attitudes influence their decision-making processes and choices. For these reasons, it is necessary to consider investors' emotions and the fact that the relationship between weather and stock returns may be justified rationally by the shift that meteorological conditions create in investors' moods.

Larissa and Tiedens (2001) have suggested that emotions influence the decision-making process. In particular, positive emotions provoke a sense of certainty, and consequently, agents utilise a heuristic processing approach, based on their knowledges. On the other hand, negative emotions induce a feeling of uncertainty, pushing agents to use a systematic processing approach and more scrutiny. By considering different kinds of emotions Gino, Brooks, and Schweitzer (2012) have demonstrated that anxiety plays a major role in the decision-making process. It makes investors more keen to seek advice, regardless of the quality of the advice.

The previously mentioned assumption that mood influences agents' risk attitudes and Kliger and Levy's (2003) demonstration that weather conditions influence investors' moods leads to the following hypothesis: a relationship, which could also be spurious and not direct, exists between weather factors and stock returns.

2.4 Differences between Italy and the Netherlands

The life and hospitality of the Netherlands and Italy are mutually exclusive, mostly due to the culture and way of life that the people live. Studies show that the concept of individuality in the European countries began in Sweden and Norway and then slowly permeated through France and the Netherlands (Gierveld & Tilburg, 1999). The southern part of Europe is still dragging behind and is still represented by more formal traditional family systems.

The population of these 2 European countries is as follows;

i) Italy has a population of 60,795,612 people, a geographic area of 301,338 km2 and a population density of 201,3 pp/km2

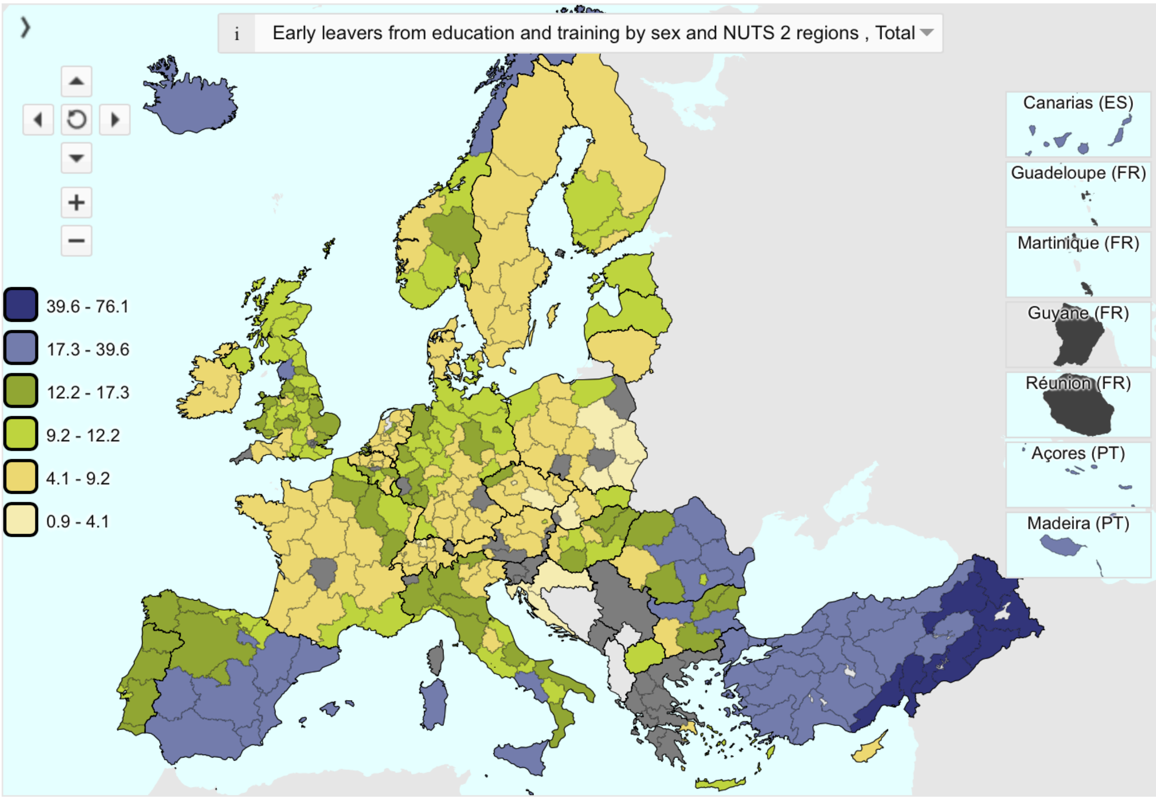
ii) The Netherlands has a population of 16,900,726, a geographical area of 41,543 km2 and a population density of 408,1 pp/km2.

Therefore, Italy is a bigger country but with less concentrated population on the territory than the Netherlands. Surveys show that some cultural differences in the social aspects of living arrangements for adults in these two nations exist, where a bigger percentage of older people living alone is higher in the Netherlands while in Italy, the population of the elderly people living with their children is greater (Mills et al., 2008). In recent years, fertility percentages in most European countries have fallen to an all-time low, that it is beyond recovery, that it has been declared a fertility crisis (Mills et al., 2008). The consequences are a high number of older people that dominate these countries. Marrying and remarrying in European countries, in general, has declined.

The cost of having children in these countries has been considered as a major factor that has contributed to this fertility problem. Older adults provide for their aged parents, therefore, do not have time to take care of children. Though the intentions are always in the right place, the adverse effects it has on the economy, and also the emotional aspects of the people, is clearly evident that things would have been done differently (Mills et al., 2008). The issue of ill health rate is higher as the population is older. This also affects the economic status of the countries (Kunst & Mackenbach, 1994).

Another major factor affecting is the education level of the citizens in these countries. Research shows that the Netherlands is doing better at education level than Italy. But overall there is still a worrying percentage of education students that never get to complete elementary education (Kunst & Mackenbach, 1994). There is a high proportion of the older people living by themselves without their partners in the Netherlands than can be found in Italy, whereas in Italy the percentage of older people who do not have partners and live with their children is higher compared to Netherlands. This could be due to the fact that there are larger family sizes in Italy than can be found in the Netherlands, although statistics have however shown that larger family sizes are highly within the Dutch elderly than with the Italians (Choi et al., 2014).

Economic reasons could further play a role in this. Joint living in a household with the older people and adult children could be a way to which they support one another where resources are not sufficient enough (l'Haridon & Vieider, 2016). There are virtually no institutional procedures for the housing of older adults in Italy as compared to the Netherlands (Dohmen et al., 2010; Benjamin et al., 2013). Home ownership in Italy thus is almost twice that in the Netherlands, despite the fact that the Netherlands has a considerably higher education level than Italy (Anderson et al., 2015). The fact that the Netherlands has a considerably higher education level than Italy can also be noticed in the interactive visualization obtained from the Eurostat site which represents the percentages of early leavers from education and trading in several European countries. It is possible to notice that the percentages are higher in Italy compared to the Netherlands.



3 Data

3.1 Financial Data

Different sources of data were used in the current research. The first source was the stock returns for the closing and opening prices of the AEX and FTSEMIB indexes, which were collected from Bloomberg. The AEX is a market capitalization weighted index of leading Dutch stocks that are traded on the Amsterdam exchange. The FTSEMIB is a market capitalization index that includes the forty most liquid and capitalized stocks listed on the Milan exchange.

The timeframe analysed was from January 1st, 2005 to December 31st, 2015 for both indexes, as this time horizon do not contain missing observations. A total of 2,816 observations were collected from the AEX index, and 2,792 observations were collected from the FTSEMIB index. The discrepancy in the number of observations is likely the result of a different number of national holidays in the two countries. The variable R_t indicates the log return of both the AEX and FTSEMIB indexes on date *t*.

Figure 1

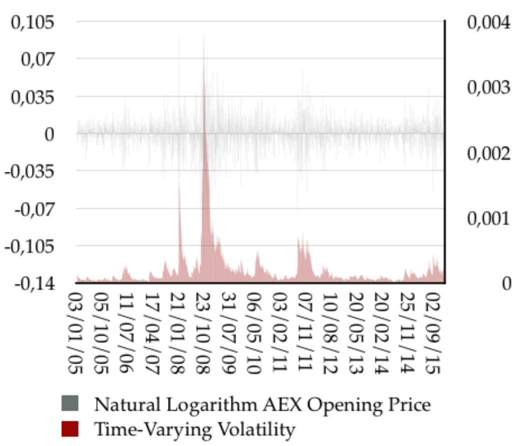
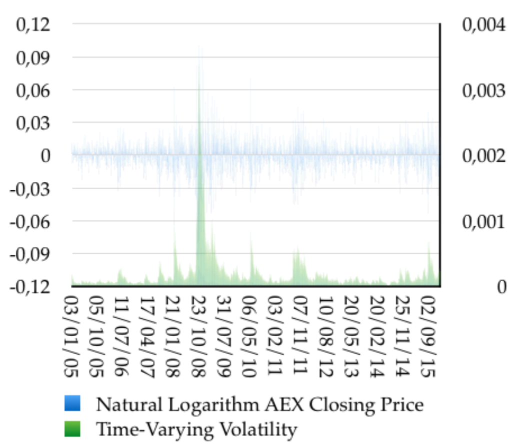


Figure 2



The grey lines in Figures 1 and 3 are the time series of the natural logarithm of the AEX and FTSEMIB stock returns in the opening hours. The blue lines in Figures 2 and 4 are the time series of the natural logarithm of the AEX and FTSEMIB stock returns.

Figure 3

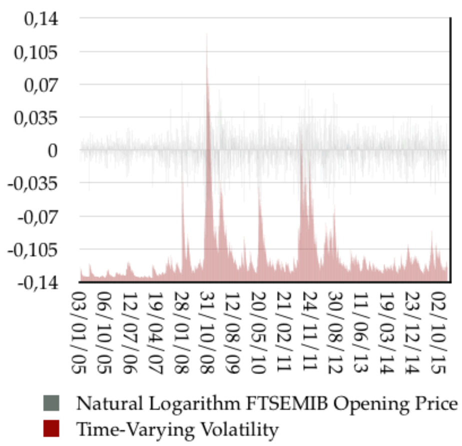
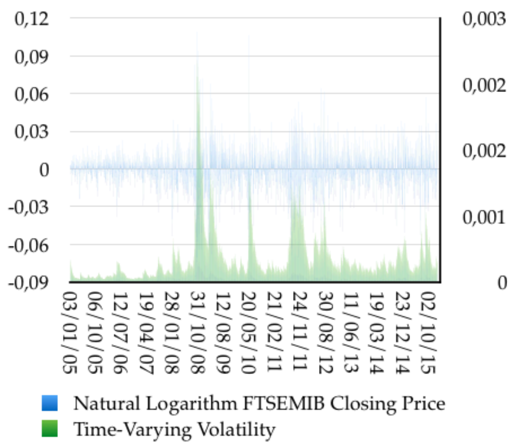


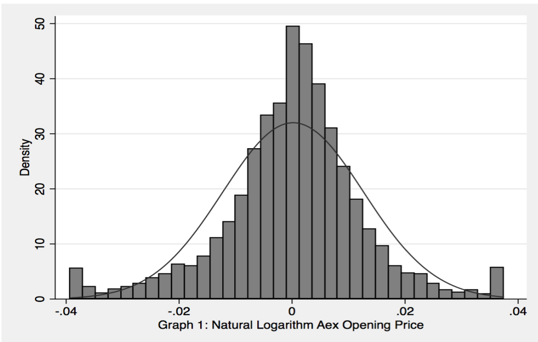
Figure 4



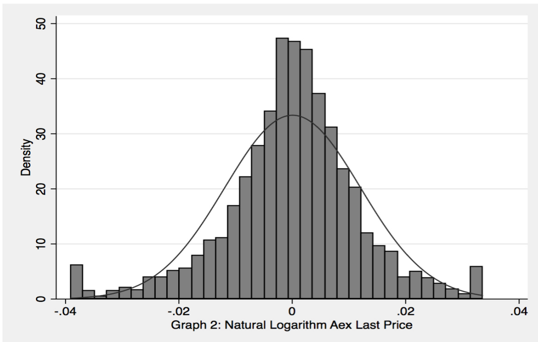
The red areas in Figures 1 and 3 represent the time-varying volatility, while In Figures 2 and 4 is represented by the green area. The time-varying volatility was derived using a GARCH (1,1) model, which is elaborated on in the following sections.

In the box plot of the time series, it is possible to identify the presence of outliers. The extreme values of these observations could have affected the results, especially in the hypothesis-testing phase. For this reason, a windsorisation process was implemented on all financial variables. Each variable was winsorised at the 1st and the 99th percentiles to exclude possible outliers.

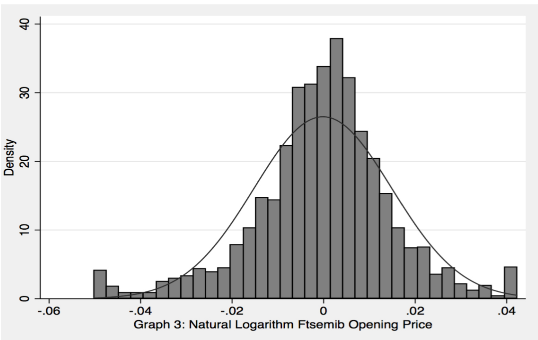
Graphs 1 to 4 illustrate the distribution of indexes stock returns indexes after the procedure was performed. In all four distributions, excess kurtosis and, consequently fat tails exist. However, pronounced skewness is not present in any distribution; this result suggests that logarithmic transformation was appropriate in this study.



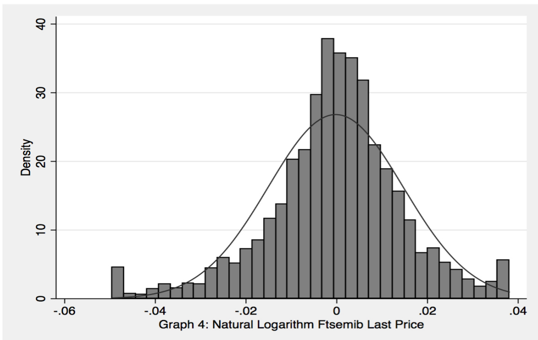
Graph 1: Natural Logarithm Aex Opening Price



Graph 2: Natural Logarithm Aex Last Price



Graph 3: Natural Logarithm Ftsemib Opening Price



Graph 4: Natural Logarithm Ftsemib Last Price

3.2 Weather Data

The Dutch company MeteoGroup provided the weather data. The data consisted of hourly observations for four different variables present in both the Amsterdam Schipol and Milano Malpensa airports from January 1st, 1957 to December 31st, 2015. The variables of interest that were analysed in the current study were wind speed, cloudiness, temperature, and precipitation.

Wind speed was expressed in knots; one knot is equal to 1,852 km/hr. Cloudiness was expressed in oktas and ranged from 0, meaning no clouds, to 8, meaning fully cloudy. Temperature was expressed in degrees Celsius. Precipitation was measured as millimetres of rain accumulated on the ground in the six hours before the data was acquired.

A data manipulation process was performed to transform the timeframe from hourly to daily. The process consisted of taking the average of each weather variable of the six hours before the market's opening, to confront them with the opening prices. While, to study the relation of the climate variables with the daily stock returns deviations, the process consisted of taking the average of each variable from 9:00 to 18:00.

Using the set of variables, I constructed another variable called degree of sunshine because I sought to examine the relationship between stock returns and sunshine. Specifically, the variable degree of sunshine is a dummy variable, which assumed a value of one when precipitation assumed a value zero, cloudiness was less than two, and wind speed was below the 25th percentile on the overall distribution.

Additionally, to examine whether the effect of weather changes persisted over longer periods, a moving average variable was created for each weather variable at seven and fourteen days. These variables can be used to understand whether persistent and adverse meteorological conditions influence investors' moods and, consequently, stock returns.

Once the two blocks of core variables were defined, I incorporated a set of exogenous variables in the analysis. These variables included a constant term, day of the week dummies, month dummies, holiday dummies, and two more dummies indicating whether date t was close to a full or new moon. I constructed these two variables using the lunar phase calendar.

3.3 Summary Statistics

Tables 1 and 2 present sample statistics for my financial and weather variables. Panel A in Table 1 illustrates that over the entire sample period, the average stock returns on the AEX index were positive for both the opening and closing prices. Panel B in Table 2 illustrates that over the entire sample period, the average stock returns on the FTSEMIB index were negative for both the opening and closing prices. Moreover, in looking at the standard deviations of the two indexes, it is clear that the stock returns on the FTSEMIB index varied more than those on the AEX index for both the opening and closing prices.

Panels B and C in Tables 1 and 2 illustrate that over the entire sample period, wind speed and cloudiness were higher on average in Amsterdam for both opening closing prices; temperature, and degree of sunshine were higher in Milan for both the opening and closing prices. Precipitation is slightly higher in Milan than in Amsterdam for both opening and closing prices.

From the summary statistics, it can be concluded that the weather conditions are more favourable in Milan than in Amsterdam. Moreover, it is important to note that the standard deviations of all the variables are higher in Milan than in Amsterdam. However, the standard deviation is a measure, which relates to the mean. To confront the data without committing errors, I should calculate the coefficient of variation for each variable. Nevertheless, confronting the meteorological conditions in these two locations was not the purpose of this study.

Table 1

Summary Statistics

AEX Index & Amsterdam-Schipol's Weather				
Panel A. Financials				
	Mean	Stand. Dev.	Min	Max
Natural logarithm AEX Closing Price	0,0000636	0,0119553	-0,0390612	0,0335547
Squared Natural logarithm AEX Closing Price	0,0001573	0,0003435	1,34E-08	0,0023778
Natural logarithm AEX Opening Price	0,0001917	0,0124648	-0,0392925	0,0374083
Squared Natural logarithm AEX Closing Price	0,0001679	0,0003596	9,83E-09	0,0023417
Panel B. Opening Hours Weather				
	Mean	Stand. Dev.	Min	Max
Wind Speed (knots)	9,39	4,94	0,00	33,52
Cloudiness	5,26	2,85	0,00	8,00
Temperature	10,30	6,46	-12,48	26,95
Precipitation	0,53	2,12	0,00	56,00
Degree of Sunshine	0,13	0,34	0,00	1,00
Panel C. Daily Weather				
	Mean	Stand. Dev.	Min	Max
Wind Speed (knots)	11,11	4,77	0,00	40,62
Cloudiness	5,14	2,55	0,00	8,00
Temperature	12,55	6,81	-6,46	31,97
Precipitation	1,11	3,23	0,00	56,00
Degree of Sunshine	0,10	0,30	0,00	1,00
# Obs 2816				

Table 2

Summary Statistics

FTSEMIB Index & Milano-Malpensa's Weather				
Panel A .Financials				
	Mean	Stand. Dev.	Min	Max
Natural logarithm FTSEMIB Closing Price	-0,000224	0,0148754	-0,0494666	0,0380648
Squared Natural logarithm FTSEMIB Closing Price	0,0002347	0,0004658	2,71E-08	0,0029951
Natural logarithm FTSEMIB Opening Price	-0,0001514	0,0150544	-0,0501321	0,0422466
Squared Natural logarithm FTSEMIB Closing Price	0,0002392	0,0004889	1,65E-08	0,0030769
Panel B. Opening Hours Weather				
	Mean	Stand. Dev.	Min	Max
Wind Speed	2,67	1,95	0,00	19,67
Cloudiness	3,21	2,98	0,00	8,00
Temperature	11,52	8,79	-12,87	29,82
Precipitation	0,97	6,90	0,00	139,00
Degree of Sunshine	0,39	0,49	0,00	1,00
Panel C. Daily Weather				
	Mean	Stand. Dev.	Min	Max
Wind Speed	3,81	2,29	0,00	22,59
Cloudiness	3,35	2,75	0,00	8,00
Temperature	16,13	8,77	-4,44	34,68
Precipitation	2,05	11,61	0,00	219,00
Degree of Sunshine	0,31	0,46	0,00	1,00
# Obs 2792				

4 Methodology and Results

Through all our analysis we will use the following specification:

$$R_t = \eta \mathcal{L}_s(R_t) + \gamma \mathcal{L}_s(R_t^2) + \beta_r(W_t) + \vartheta X_t + \epsilon_t \qquad (1)$$

Where $\mathcal{L}_s$ denotes a lag operator depending on s, which identifies the number of lags. In our case s assumes values from 1 to 5. R_t denotes the log returns of AEX or FTSEMIB indexes, depending on the case. R_t^2 denotes the squared log returns of AEX or FTSEMIB indexes, we include the lags of the square returns due to we consider them as a proxy for the volatility. The vector W_t denotes the set of weather variables: Wind Speed, Cloudiness, Temperature, Precipitation and Degree of Sunshine. Furthermore, the former vector includes a 7 and 14 days moving average for each variable. The moving averages of the weather variables are added in the analysis to study if the effect persist in time. The vector X_t denotes the set of exogenous variables including day-of-the-week dummy, month dummy, holiday dummy, and lunar phases dummy. Lastly, ϵ_t is the error term with zero mean with the possibility of time-varying volatility.

The analysis consists of a series of regressions for which I run a specification and an heteroskedasticity tests. Following the results of these tests and to correctly interpret the parameters the standard errors of the estimated coefficients in the regressions are clustered on the variable month. This procedure allows to correctly interpret the coefficients by limiting the biasing effect given by the presence of heteroskedasticity. An additional robustness test is performed consisting in the application of a generalised autoregressive heteroskedasticity consistent model to the data, which will be explained later.

4.1 Regression Estimates

Table 3 Panel A shows that the coefficient of the variable Wind Speed for the opening hours is significantly different from 0 at the 0,05 level (p-value <0,05), with a negative sign. This means that ceteris paribus, an increase in the average Wind Speed in the six hours before the opening of the market will result in a decrease on the returns of the AEX index of 1,35 basis points. However, the Wind Speed is the only variable, whose coefficient is significantly different from zero for the opening hours. Table 3 Panel A also shows that the coefficient of the variable Temperature for the daily hours is significantly different from 0 at the 0,05 level, with a negative sign. This means that ceteris paribus, an increase in the average Temperature during the hours in which the market is open, will decrease the returns on the AEX index of 1,5 basis points.

In order to assert that our results are valid, we perform an heteroskedasticity test and a Specification test. Table 3 Panel B shows the results of both test. The Null hypothesis of constant variance is rejected both for the opening and daily hours. The Null hypothesis of no omitted variables is rejected both for the opening and daily hours. The specification test, namely the Ramsey RESET test, is a general test and the reason for its rejection could be various as also heteroskedasticity could play a role in it.

Table 3

Regression

AEX Index	Opening Hours		Daily Hours	
Panel A. Regression				
	β	***t-stat***	***β***	***t-stat***
Wind Speed	-0,000135*	-2,48	-0,000044	-0,85
Cloudiness	-0,000024	-0,22	-0,000099	-0,84
Temperature	-0,000044	-0,55	-0,000150*	-2,06
Precipitation	0,000112	0,98	0,000003	0,51
Degree of Sunshine	-0,001325	-1,38	0,000187	0,19
Panel B. Tests				
	Chi-stat/F-stat	***p-value***	***Chi-stat/F-stat***	***p-value***
*Heteroskedasticity Test**	3,03	0,00	22,54	0,00
*Ramsey Reset Test***	8,35	0,00	6,52	0,00

**Breusch-Pagan / Cook-Weisberg test ((Null Hypothesis: Constant Variance)*
***Specification test(Null Hypothesis: No omitted variables)*

$*p < 0,05$; $**p < 0,01$

Table 4 Panel A shows that the coefficients of all the variables are not significantly different from zero for both opening and daily hours. This means that any changes in the weather variables have no impact on the returns on the FTSEMIB Index.

Table 4

Regression

FTSEMIB Index	Opening Hours		Daily Hours	
Panel A. Regression				
	β	***t-stat***	***β***	***t-stat***
Wind Speed	-0,000008	-0,48	-0,000154	-0,99
Cloudiness	-0,000146	-0,87	-0,000120	-0,68
Temperature	-0,000089	-0,88	-0,000093	-0,94
Precipitation	0,000039	0,63	0,000015	0,63
Degree of Sunshine	-0,000153	-0,15	-0,000628	-0,65
Panel B. Tests				
	Chi-stat/F-stat	***p-value***	***Chi-stat/F-stat***	***p-value***
*Heteroskedasticity Test**	0,54	0,46	1,58	0,20
*Ramsey Reset Test***	3,89	0,00	3,76	0,01

**Breusch-Pagan / Cook-Weisberg test ((Null Hypothesis: Constant Variance)*
***Specification test(Null Hypothesis: No omitted variables)*

$^*p < 0,05$; $^{**}p < 0,01$

Table 4 Panel B shows the results of both Heteroskedasticity and Specification test. Here we cannot reject the Null hypothesis of constant variance both for the opening and daily hours. However, the Null hypothesis of no omitted variables is rejected both for the opening and daily hours. The RESET test is a general test, and its rejection together with the non-rejection of the Null hypothesis of constant variance, suggest to step further in the analysis and account anyway for heteroskedasticity.

4.2 Regression Estimates with Clustered Standard Error

In order to limit the problem of heteroskedasticity, we once again run the regression in specification (1) using clustered standard errors on the variable Month. This operation allows us to account for the fact that the volatility of stock returns could vary from month to month.

Table 5

Regression with clustered standard error

AEX Index	Opening Hours		Daily Hours	
Panel A. Heteroskedasticity-consistent Regression				
	ß	***t-stat***	***ß***	***t-stat***
Wind Speed	-0,000135*	-1,90	-0,000044	-0,80
Cloudiness	-0,000024	-0,25	-0,000099	-1,16
Temperature	-0,000044	-0,66	-0,000150*	-2,38
Precipitation	0,000112	1,14	0,000003	1,52
Degree of Sunshine	-0,001325	-1,18	0,000187	0,19
Panel B. Tests				
	F-stat	***p-value***	***F-stat***	***p-value***
*ß-Temperature**	0,44	0,52	5,65	0,03
*ß-Wind Speed+ß-Temperature***	5,21	0,04	5,48	0,03

**(Null: ß=0)*
***(Null: sum of ß= 0)*

$^*p < 0,05$; $^{**}p < 0,01$

Table 5 Panel A shows that the coefficient of the variable Wind Speed in the opening hours and the one of the variable Temperature for the daily hours are still significantly different from 0 at the 0,05 level (p-value <0,05), even after accounting for heteroskedasticity. This means that the interpretation of the coefficients does not change.

In order to test if the joint effect of some variable is significant we employ an F-test. Table 5 Panel B shows that, even if the coefficient of the variable Temperature is not significantly different from 0 in the opening hours and the coefficient of the variable Wind Speed is not significantly different from 0 in the daily hours, the joint effect of the variable Wind Speed and Temperature is significantly different from zero both in the opening and in the daily hours.

Table 6 Panel A shows that once again all the coefficients of the weather variables for the FTSEMIB index are not significantly different from zero, both for the opening and closing hours.

However, Table 6 Panel B shows that the joint effect of the variable Wind Speed and Temperature is significantly different from 0 in the daily hours. This suggests that rather than controlling for the singular effect of each variable, to better understand the effect of the weather on stock returns we should control for the joint effect of these variables as suggested by Yoon and Kang (2009).

Table 6

Regression with clustered standard error

FTSEMIB Index	Opening Hours		Daily Hours	
Panel A. Heteroskedasticity-consistent Regression				
	ß	***t-stat***	***ß***	***t-stat***
Wind Speed	-0,000008	-0,34	-0,000154	-1,11
Cloudiness	-0,000146	-0,89	-0,0001203	-0,48
Temperature	-0,000089	-0,83	-0,0000936	-1,10
Precipitation	0,000039	1,49	0,0000158	0,56
Degree of Sunshine	-0,000153	-0,21	-0,0006289	-0,41
Panel B. Tests				
	F-stat	***p-value***	***F-stat***	***p-value***
*ß-Temperature**	0,69	0,42	1,20	0,29
*ß-Wind Speed+ß-Temperature***	0,53	0,48	4,54	0,05

**(Null: ß=0)*
***(Null: sum of ß= 0)*

**p < 0,05; **p < 0,01*

4.3 Regression Estimates with Constant Variance

Despite we clustered our standard errors to avoid the obstacles imposed by the presence of heteroskedasticity, one could be concerned that periods of high volatility could influence our outcomes. To address such concern I fitted a generalised autoregressive heteroskedasticity consistent model to both the AEX and FTTSEMIB indexes, obtaining for each index and for both opening and closing prices different time series of time varying volatility. Then I divided the stock returns for the series of time varying volatility, we obtain a time series of stock returns with volatility normalised to unity. Applying a GARCH model allows the researcher to take into account the variation of the volatility during time to limit the effect of distortion in the p-values of the estimated coefficients given by the presence of heteroskedasticity.

Table 7

Regression with constant variance

AEX Index	Opening Hours		Daily Hours	
Panel A. Constant Variance Regression				
	ß	***t-stat***	***ß***	***t-stat***
Wind Speed	-0,128564*	-2,43	-0,004653	-0,93
Cloudiness	-0,001880	-0,24	-0,002510	-0,36
Temperature	0,000262	0,04	-0,007130	-1,23
Precipitation	0,010979	1,14	0,004688	2,47
Degree of Sunshine	-0,011584	-1,28	-0,004765	-0,08
Panel B. Tests				
	F-stat	***p-value***	***F-stat***	***p-value***
*ß-Temperature**	0,00	0,96	1,50	0,24
*ß-Wind Speed+ß-Temperature***	3,13	0,10	2,36	0,15
(Null: ß=0)* *(Null: sum of ß= 0)*				
Panel C. Garch (1,1) Estimates				
	ω,α,β		***ω,α,β***	
Constant, ω	0,0064		0,0026	
Innovations term, α	0,0781		0,0978	
Autoregressive term, ß	0,9210		0,9001	

**p < 0,05; **p < 0,01*

The estimated coefficients for the GARCH (1,1) model for the AEX index are given in Panel C of Table 7, while those for the FTSEMIB index are given in Panel C of Table 8.

Table 7 Panel A shows that the coefficient for the variable Wind Speed for the opening hours is still significantly different from 0 at 0,05 level, even after this robustness test. However, Table 7 Panel B shows that the results of the F-test are not significant anymore.

Table 8

Regression with constant variance

FTSEMIB Index	Opening Hours		Daily Hours	
Panel A. Constant Variance Regression				
	β	***t-stat***	***β***	***t-stat***
Wind Speed	-0,003447	-0,26	-0,014381	-1,72
Cloudiness	-0,011923	-1,08	-0,015064	-0,90
Temperature	-0,007553	-1,01	-0,009566	-1,89
Precipitation	0,002974	1,79	0,002155	0,99
Degree of Sunshine	0,005606	0,10	-0,063235	-0,67
Panel B. Tests				
	F-stat	***p-value***	***F-stat***	***p-value***
*ß-Temperature**	1,02	0,33	3,56	0,08
*ß-Wind Speed+ß-Temperature***	0,61	0,45	10,47	0,00

**(Null: ß=0)*
***(Null: sum of ß= 0)*

Panel C. Garch(1,1) Estimates		
	ω,α,β	***ω,α,β***
Constant, ω	0,0049	0,0054
Innovations term, α	0,0866	0,0778
Autoregressive term, ß	0,9115	0,9221

**p < 0,05; **p < 0,01*

Table 8 Panel A shows that all the coefficients of the variable for both opening and closing price are not significantly different from 0. However, from Table 8 Panel B we can see that the F-test for the interaction of the coefficient of Wind Speed and Temperature is significantly different from 0 at 0,01 level (p-value <0,01). The results for this section suggest once again that the interaction of the weather variables has a stronger impact than the individual variables.

4.4 Regression Estimates by Month

An additional robustness test is performed, consisting in regressing the specification (1) by month, clustering the standard errors on the variable years and executing it with both time-varying variance and constant variance.

However, the results are mixed and the Stata code used to obtain them and recreate all the analysis can be found in the Appendix. The reason for these mixed result could be mainly because repeating the regression for each month implies considering only the observations belonging to that month. This operation facilitates the rejection of the null hypothesis for each coefficient estimated due to the small sample size and could bias the results.

5 Discussion and Conclusion

The results of our analysis strongly support the influence of the variable wind speed on the AEX index stock returns in the opening hours. Moreover, testing for the significance of the sum of the coefficients of different variables, it is possible to notice that, in several instances, the interaction of wind speed and temperature is statistically different from zero.

Nevertheless, considering the significance of the coefficients, the only one which surpasses all the robustness tests is the estimated coefficient of the wind speed for the opening hours. Regarding the FTSEMIB index, there are no factors associated with weather conditions that seem to influence the stock returns significantly.

A strong point of this study is that the data regarding the Netherlands for the weather variable is accurate and, due to the restricted area of the country, it can be accounted to be worth all the financial firms operating in the Amsterdam Stock Exchange. The measure of cloudiness used can assume values from 1 to 8, which is the same measurement used by Hirshleifer and Shumway (2013). Saunders (1993) measures the cloudiness with three categories of percentages (0%-30%, 40%-70%, 80%-100%), which do not differ consistently in accuracy from the data used in this study. It is possible to assert that when controlling for wind speed in the Netherlands, cloudiness does not influence the stock market index anymore and that the meteorological variable influencing the most Dutch investors' mood is the wind speed. The influence of the variable wind speed on investors' mood translate in a variation on the index stock market returns.

However, with respect to Hirshleifer and Shumway (2013), to improve the accuracy of the analysis other variables, such as the barometric pressure, could be added. Another finding of this study, which is also confirmed by Chang, Nieh, and Yang (2006), is that the interaction of multiple weather variables has a stronger effect than the impact of each individual one, interactions variables could be added in future researches.

Nonetheless, even if the results for the Netherlands are robust and significant, a weak point of this study is the analysis on the FTSEMIB, not due to the insignificance of the parameters but due to the fact that the weather variables were collected for the geographical area of Milan, and while the Italian territory is wider, the same weather conditions cannot be accounted for to be the same for all the investors operating in the market. To improve the accuracy of the study for further research, only the investors operating in the market and belonging to the Lombardia region, which has a similar population and geographical area as the Netherlands, consequently making the two comparable, should be taken into consideration. However, obtaining this data could be difficult or impossible due to the presence of private firms operating as investors in the market.

The goal of this research was to explore whether meteorological conditions influence investors' moods, causing variations in the stock market index. The literature review provided evidence that weather conditions could, indeed, influence stock returns.

The regression analysis showed significant results for the AEX index, which was affected by the opening hours by the wind speed, and it demonstrated that those interactions between weather variables could better explain the effect of weather on stock returns. This study does not support Saunders (1993) findings as when controlling for the variable wind speed, the variable cloudiness does not affect anymore the stock market index returns, suggesting that investors' mood in the Netherlands is more affected by the wind speed than other meteorological conditions.

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Appendix

A.1 Stata Code AEX

```
import excel "/Users/Mirko/Desktop/Erasmus University/Thesis - Behavioural
Economics/Data_Mirko_Ravasi.xlsx", sheet("AEX") firstrow case(lower)
rename ap d_2005
rename aq d_2006
rename ar d_2007
rename as d_2008
rename at d_2009
rename au d_2010
rename av d_2011
rename aw d_2012
rename ax d_2013
rename ay d_2014
rename az d_2015
winsor2 lnr_aex_lpx lnr_aex_lpx_sq lnr_aex_oppx lnr_aex_oppx_sq s2t_lpx
s2t_oppx, cuts(1 99)
gen lnlp1= lnr_aex_lpx_w[_n-1]
gen lnlp2= lnr_aex_lpx_w[_n-2]
gen lnlp3= lnr_aex_lpx_w[_n-3]
gen lnlp4= lnr_aex_lpx_w[_n-4]
gen lnlp5= lnr_aex_lpx_w[_n-5]
gen lnlpsq1= lnr_aex_lpx_sq_w[_n-1]
gen lnlpsq2= lnr_aex_lpx_sq_w[_n-2]
gen lnlpsq3= lnr_aex_lpx_sq_w[_n-3]
gen lnlpsq4= lnr_aex_lpx_sq_w[_n-4]
gen lnlpsq5= lnr_aex_lpx_sq_w[_n-5]
gen lnop1= lnr_aex_oppx_w[_n-1]
gen lnop2= lnr_aex_oppx_w[_n-2]
gen lnop3= lnr_aex_oppx_w[_n-3]
gen lnop4= lnr_aex_oppx_w[_n-4]
gen lnop5= lnr_aex_oppx_w[_n-5]
gen lnopsq1= lnr_aex_oppx_sq_w[_n-1]
gen lnopsq2= lnr_aex_oppx_sq_w[_n-2]
gen lnopsq3= lnr_aex_oppx_sq_w[_n-3]
gen lnopsq4= lnr_aex_oppx_sq_w[_n-4]
gen lnopsq5= lnr_aex_oppx_sq_w[_n-5]
gen nlnlp= lnr_aex_lpx_w/(s2t_lpx_w^(1/2))
gen nlnlp1= nlnlp[_n-1]
gen nlnlp2= nlnlp[_n-2]
gen nlnlp3= nlnlp[_n-3]
```

```
gen nlnlp4= nlnlp[_n-4]
gen nlnlp5= nlnlp[_n-5]
gen nlnlp_sq=nlnlp^2
gen nlnlp1_sq=nlnlp1^2
gen nlnlp2_sq=nlnlp2^2
gen nlnlp3_sq=nlnlp3^2
gen nlnlp4_sq=nlnlp4^2
gen nlnlp5_sq=nlnlp5^2
gen nlnop=  lnr_aex_oppx/( s2t_oppx_w^(1/2))
gen nlnop1= nlnop[_n-1]
gen nlnop2= nlnop[_n-2]
gen nlnop3= nlnop[_n-3]
gen nlnop4= nlnop[_n-4]
gen nlnop5= nlnop[_n-5]
gen nlnop_sq=nlnop^2
gen nlnop1_sq=nlnop1^2
gen nlnop2_sq=nlnop2^2
gen nlnop3_sq=nlnop3^2
gen nlnop4_sq=nlnop4^2
gen nlnop5_sq=nlnop5^2
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gen  ff_op2= ff_op[_n-2]
gen  ff_op3= ff_op[_n-3]
gen  ff_op4= ff_op[_n-4]
gen  ff_op5= ff_op[_n-5]
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gen  ff_op10= ff_op[_n-10]
gen  ff_op11= ff_op[_n-11]
gen  ff_op12= ff_op[_n-12]
gen  ff_op13= ff_op[_n-13]
gen  ff_op14= ff_op[_n-14]
gen ff_op_7daymav=[(ff_op1+ff_op2+ff_op3+ff_op4+ff_op5+ff_op6+ff_op7)/7]
gen
ff_op_14daymav=[(ff_op1+ff_op2+ff_op3+ff_op4+ff_op5+ff_op6+ff_op7+ff_op8+f
f_op9+ff_op10+ff_op11+ff_op12+ff_op13+ff_op14)/14]
gen  ne_op1= ne_op[_n-1]
gen  ne_op2= ne_op[_n-2]
gen  ne_op3= ne_op[_n-3]
gen  ne_op4= ne_op[_n-4]
gen  ne_op5= ne_op[_n-5]
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gen  ne_op7= ne_op[_n-7]
gen  ne_op8= ne_op[_n-8]
gen  ne_op9= ne_op[_n-9]
gen  ne_op10= ne_op[_n-10]
gen  ne_op11= ne_op[_n-11]
```

```
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gen  ne_op13= ne_op[_n-13]
gen  ne_op14= ne_op[_n-14]
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ne_op_7daymav=[(ne_op1+ne_op2+ne_op3+ne_op4+ne_op5+ne_op6+ne_op7)/7]
gen
ne_op_14daymav=[(ne_op1+ne_op2+ne_op3+ne_op4+ne_op5+ne_op6+ne_op7+n
e_op8+ne_op9+ne_op10+ne_op11+ne_op12+ne_op13+ne_op14)/14]
gen  tt_op1= tt_op[_n-1]
gen  tt_op2= tt_op[_n-2]
gen  tt_op3= tt_op[_n-3]
gen  tt_op4= tt_op[_n-4]
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gen  tt_op9= tt_op[_n-9]
gen  tt_op10= tt_op[_n-10]
gen  tt_op11= tt_op[_n-11]
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gen  tt_op13= tt_op[_n-13]
gen  tt_op14= tt_op[_n-14]
gen tt_op_7daymav=[(tt_op1+tt_op2+tt_op3+tt_op4+tt_op5+tt_op6+tt_op7)/7]
gen
tt_op_14daymav=[(tt_op1+tt_op2+tt_op3+tt_op4+tt_op5+tt_op6+tt_op7+tt_op8+tt
_op9+tt_op10+tt_op11+tt_op12+tt_op13+tt_op14)/14]
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gen  rrr6_op3= rrr6_op[_n-3]
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gen  rrr6_op5= rrr6_op[_n-5]
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gen  rrr6_op9= rrr6_op[_n-9]
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gen  rrr6_op13= rrr6_op[_n-13]
gen  rrr6_op14= rrr6_op[_n-14]
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r6_op7)/7]
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rrr6_op7+rrr6_op8+rrr6_op9+rrr6_op10+rrr6_op11+rrr6_op12+rrr6_op13+rrr6_op
14)/14]
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gen  sunshine_op2= sunshine_op[_n-2]
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```
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gen  sunshine_op8= sunshine_op[_n-8]
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gen  sunshine_op10= sunshine_op[_n-10]
gen  sunshine_op11= sunshine_op[_n-11]
gen  sunshine_op12= sunshine_op[_n-12]
gen  sunshine_op13= sunshine_op[_n-13]
gen  sunshine_op14= sunshine_op[_n-14]
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sunshine_op_7daymav=[(sunshine_op1+sunshine_op2+sunshine_op3+sunshine_
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gen
sunshine_op_14daymav=[(sunshine_op1+sunshine_op2+sunshine_op3+sunshine_
op4+sunshine_op5+sunshine_op6+sunshine_op7+sunshine_op8+sunshine_op9+s
unshine_op10+sunshine_op11+sunshine_op12+sunshine_op13+sunshine_op14)/1
4]
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gen  ff_dy6= ff_dy[_n-6]
gen  ff_dy7= ff_dy[_n-7]
gen  ff_dy8= ff_dy[_n-8]
gen  ff_dy9= ff_dy[_n-9]
gen  ff_dy10= ff_dy[_n-10]
gen  ff_dy11= ff_dy[_n-11]
gen  ff_dy12= ff_dy[_n-12]
gen  ff_dy13= ff_dy[_n-13]
gen  ff_dy14= ff_dy[_n-14]
gen ff_dy_7daymav=[(ff_dy1+ff_dy2+ff_dy3+ff_dy4+ff_dy5+ff_dy6+ff_dy7)/7]
gen
ff_dy_14daymav=[(ff_dy1+ff_dy2+ff_dy3+ff_dy4+ff_dy5+ff_dy6+ff_dy7+ff_dy8+f
f_dy9+ff_dy10+ff_dy11+ff_dy12+ff_dy13+ff_dy14)/14]
gen  ne_dy1= ne_dy[_n-1]
gen  ne_dy2= ne_dy[_n-2]
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gen  ne_dy4= ne_dy[_n-4]
gen  ne_dy5= ne_dy[_n-5]
gen  ne_dy6= ne_dy[_n-6]
gen  ne_dy7= ne_dy[_n-7]
gen  ne_dy8= ne_dy[_n-8]
gen  ne_dy9= ne_dy[_n-9]
gen  ne_dy10= ne_dy[_n-10]
gen  ne_dy11= ne_dy[_n-11]
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gen  ne_dy12= ne_dy[_n-12]
gen  ne_dy13= ne_dy[_n-13]
gen  ne_dy14= ne_dy[_n-14]
gen
ne_dy_7daymav=[(ne_dy1+ne_dy2+ne_dy3+ne_dy4+ne_dy5+ne_dy6+ne_dy7)/7]
gen
ne_dy_14daymav=[(ne_dy1+ne_dy2+ne_dy3+ne_dy4+ne_dy5+ne_dy6+ne_dy7+n
e_dy8+ne_dy9+ne_dy10+ne_dy11+ne_dy12+ne_dy13+ne_dy14)/14]
gen  tt_dy1= tt_dy[_n-1]
gen  tt_dy2= tt_dy[_n-2]
gen  tt_dy3= tt_dy[_n-3]
gen  tt_dy4= tt_dy[_n-4]
gen  tt_dy5= tt_dy[_n-5]
gen  tt_dy6= tt_dy[_n-6]
gen  tt_dy7= tt_dy[_n-7]
gen  tt_dy8= tt_dy[_n-8]
gen  tt_dy9= tt_dy[_n-9]
gen  tt_dy10= tt_dy[_n-10]
gen  tt_dy11= tt_dy[_n-11]
gen  tt_dy12= tt_dy[_n-12]
gen  tt_dy13= tt_dy[_n-13]
gen  tt_dy14= tt_dy[_n-14]
gen tt_dy_7daymav=[(tt_dy1+tt_dy2+tt_dy3+tt_dy4+tt_dy5+tt_dy6+tt_dy7)/7]
gen
tt_dy_14daymav=[(tt_dy1+tt_dy2+tt_dy3+tt_dy4+tt_dy5+tt_dy6+tt_dy7+tt_dy8+t
t_dy9+tt_dy10+tt_dy11+tt_dy12+tt_dy13+tt_dy14)/14]
gen  rrr6_dy1= rrr6_dy[_n-1]
gen  rrr6_dy2= rrr6_dy[_n-2]
gen  rrr6_dy3= rrr6_dy[_n-3]
gen  rrr6_dy4= rrr6_dy[_n-4]
gen  rrr6_dy5= rrr6_dy[_n-5]
gen  rrr6_dy6= rrr6_dy[_n-6]
gen  rrr6_dy7= rrr6_dy[_n-7]
gen  rrr6_dy8= rrr6_dy[_n-8]
gen  rrr6_dy9= rrr6_dy[_n-9]
gen  rrr6_dy10= rrr6_dy[_n-10]
gen  rrr6_dy11= rrr6_dy[_n-11]
gen  rrr6_dy12= rrr6_dy[_n-12]
gen  rrr6_dy13= rrr6_dy[_n-13]
gen  rrr6_dy14= rrr6_dy[_n-14]
gen
rrr6_dy_7daymav=[(rrr6_dy1+rrr6_dy2+rrr6_dy3+rrr6_dy4+rrr6_dy5+rrr6_dy6+r
rr6_dy7)/7]
gen
rrr6_dy_14daymav=[(rrr6_dy1+rrr6_dy2+rrr6_dy3+rrr6_dy4+rrr6_dy5+rrr6_dy6+
rrr6_dy7+rrr6_dy8+rrr6_dy9+rrr6_dy10+rrr6_dy11+rrr6_dy12+rrr6_dy13+rrr6_dy
14)/14]
rename sunshine_lp sunshine_dy
gen  sunshine_dy1= sunshine_dy[_n-1]
```

```
gen  sunshine_dy2= sunshine_dy[_n-2]
gen  sunshine_dy3= sunshine_dy[_n-3]
gen  sunshine_dy4= sunshine_dy[_n-4]
gen  sunshine_dy5= sunshine_dy[_n-5]
gen  sunshine_dy6= sunshine_dy[_n-6]
gen  sunshine_dy7= sunshine_dy[_n-7]
gen  sunshine_dy8= sunshine_dy[_n-8]
gen  sunshine_dy9= sunshine_dy[_n-9]
gen  sunshine_dy10= sunshine_dy[_n-10]
gen  sunshine_dy11= sunshine_dy[_n-11]
gen  sunshine_dy12= sunshine_dy[_n-12]
gen  sunshine_dy13= sunshine_dy[_n-13]
gen  sunshine_dy14= sunshine_dy[_n-14]
gen
sunshine_dy_7daymav=[(sunshine_dy1+sunshine_dy2+sunshine_dy3+sunshine_
dy4+sunshine_dy5+sunshine_dy6+sunshine_dy7)/7]
gen
sunshine_dy_14daymav=[(sunshine_dy1+sunshine_dy2+sunshine_dy3+sunshine
_dy4+sunshine_dy5+sunshine_dy6+sunshine_dy7+sunshine_dy8+sunshine_dy9+
sunshine_dy10+sunshine_dy11+sunshine_dy12+sunshine_dy13+sunshine_dy14)/
14]
summarize  lnr_aex_lpx_w-lnr_aex_oppx_sq_w, format
summarize ff_op-sunshine_op,format
summarize ff_dy-sunshine_dy, format
histogram lnr_aex_lpx_w, normal scheme(sj)
(bin=34, start=-.09590334, width=.00577018)
histogram lnr_aex_oppx_w, normal scheme(sj)
(bin=34, start=-.12015719, width=.0062307)
regress  lnr_aex_lpx_w  lnlp1 lnlp2 lnlp3 lnlp4 lnlp5 lnlpsq1 lnlpsq2 lnlpsq3
lnlpsq4 lnlpsq5 ff_dy ff_dy_7daymav ff_dy_14daymav ne_dy ne_dy_7daymav
ne_dy_14daymav tt_dy tt_dy_7daymav tt_dy_14daymav rrr6_dy
rrr6_dy_7daymav rrr6_dy_14daymav sunshine_dy sunshine_dy_7daymav
sunshine_dy_14daymav  monday tuesday thursday friday january february april
may june july august september october november december holiday fullmn
newmn
estat hettest
estat ovtest
regress  lnr_aex_lpx_w  lnlp1 lnlp2 lnlp3 lnlp4 lnlp5 lnlpsq1 lnlpsq2 lnlpsq3
lnlpsq4 lnlpsq5 ff_dy ff_dy_7daymav ff_dy_14daymav ne_dy ne_dy_7daymav
ne_dy_14daymav tt_dy tt_dy_7daymav tt_dy_14daymav rrr6_dy
rrr6_dy_7daymav rrr6_dy_14daymav sunshine_dy sunshine_dy_7daymav
sunshine_dy_14daymav  monday tuesday thursday friday january february april
may june july august september october november december holiday fullmn
newmn, vce(cluster month)
test (_b[ff_dy]=0)
test (_b[ff_dy]+_b[ff_dy_7daymav]+_b[ff_dy_14daymav]=0)
test (_b[ne_dy]=0)
test (_b[ne_dy]+_b[ne_dy_7daymav]+_b[ne_dy_14daymav]=0)
test (_b[tt_dy]=0)
```

```
test (_b[tt_dy]+_b[tt_dy_7daymav]+_b[tt_dy_14daymav]=0)
test (_b[rrr6_dy]=0)
test (_b[rrr6_dy]+_b[rrr6_dy_7daymav]+_b[rrr6_dy_14daymav]=0)
test (_b[sunshine_dy]=0)
test (_b[sunshine_dy]+_b[sunshine_dy_7daymav]+_b[sunshine_dy_14daymav]=0)
test (_b[ff_dy]+_b[ne_dy]+_b[tt_dy]+_b[rrr6_dy]+_b[sunshine_dy]=0)
test (_b[ff_dy]+_b[tt_dy]=0)
regress  lnr_aex_oppx_w lnop1 lnop2 lnop3 lnop4 lnop5 lnopsq1 lnopsq2  lnopsq3
lnopsq4 lnopsq5 ff_op ff_op_7daymav ff_op_14daymav ne_op ne_op_7daymav
ne_op_14daymav tt_op tt_op_7daymav tt_op_14daymav rrr6_op
rrr6_op_7daymav rrr6_op_14daymav sunshine_op sunshine_op_7daymav
sunshine_op_14daymav  monday tuesday thursday friday january february april
may june july august september october november december holiday fullmn
newmn
estat hettest
estat ovtest
regress  lnr_aex_oppx_w lnop1 lnop2 lnop3 lnop4 lnop5 lnopsq1 lnopsq2  lnopsq3
lnopsq4 lnopsq5 ff_op ff_op_7daymav ff_op_14daymav ne_op ne_op_7daymav
ne_op_14daymav tt_op tt_op_7daymav tt_op_14daymav rrr6_op
rrr6_op_7daymav rrr6_op_14daymav sunshine_op sunshine_op_7daymav
sunshine_op_14daymav  monday tuesday thursday friday january february april
may june july august september october november december holiday fullmn
newmn, vce(cluster month)
test (_b[ff_op]=0)
test (_b[ff_op]+_b[ff_op_7daymav]+_b[ff_op_14daymav]=0)
test (_b[ne_op]=0)
test (_b[ne_op]+_b[ne_op_7daymav]+_b[ne_op_14daymav]=0)
test (_b[tt_op]=0)
test (_b[tt_op]+_b[tt_op_7daymav]+_b[tt_op_14daymav]=0)
test (_b[rrr6_op]=0)
test (_b[rrr6_op]+_b[rrr6_op_7daymav]+_b[rrr6_op_14daymav]=0)
test (_b[sunshine_op]=0)
test (_b[sunshine_op]+_b[sunshine_op_7daymav]+_b[sunshine_op_14daymav]=0)
test (_b[ff_op]+_b[ne_op]+_b[tt_op]+_b[rrr6_op]+_b[sunshine_op]=0)
test (_b[ff_op]+_b[tt_op]=0)
regress  nlnlp nlnlp1 nlnlp2 nlnlp3 nlnlp4 nlnlp5 nlnlp1_sq nlnlp2_sq nlnlp3_sq
nlnlp4_sq nlnlp5_sq ff_dy ff_dy_7daymav ff_dy_14daymav ne_dy
ne_dy_7daymav ne_dy_14daymav tt_dy tt_dy_7daymav tt_dy_14daymav rrr6_dy
rrr6_dy_7daymav rrr6_dy_14daymav sunshine_dy sunshine_dy_7daymav
sunshine_dy_14daymav  monday tuesday wednesday thursday friday january
february april may june july august september october november december
holiday fullmn newmn, vce(cluster month)
test (_b[ff_dy]=0)
test (_b[ff_dy]+_b[ff_dy_7daymav]+_b[ff_dy_14daymav]=0)
test (_b[ne_dy]=0)
test (_b[ne_dy]+_b[ne_dy_7daymav]+_b[ne_dy_14daymav]=0)
test (_b[tt_dy]=0)
test (_b[tt_dy]+_b[tt_dy_7daymav]+_b[tt_dy_14daymav]=0)
test (_b[rrr6_dy]=0)
```

```
test (_b[rrr6_dy]+_b[rrr6_dy_7daymav]+_b[rrr6_dy_14daymav]=0)
test (_b[sunshine_dy]=0)
test (_b[sunshine_dy]+_b[sunshine_dy_7daymav]+_b[sunshine_dy_14daymav]=0)
test (_b[ff_dy]+_b[ne_dy]+_b[tt_dy]+_b[rrr6_dy]+_b[sunshine_dy]=0)
test (_b[ff_dy]+_b[tt_dy]=0)
regress  nlnop nlnop1 nlnop2 nlnop3 nlnop4 nlnop5 nlnop1_sq nlnop2_sq
nlnop3_sq nlnop4_sq nlnop5_sq ff_op ff_op_7daymav ff_op_14daymav ne_op
ne_op_7daymav ne_op_14daymav tt_op tt_op_7daymav tt_op_14daymav rrr6_op
rrr6_op_7daymav rrr6_op_14daymav sunshine_op sunshine_op_7daymav
sunshine_op_14daymav  monday tuesday wednesday thursday friday january
february april may june july august september october november december
holiday fullmn newmn, vce(cluster month)
test (_b[ff_op]=0)
test (_b[ff_op]+_b[ff_op_7daymav]+_b[ff_op_14daymav]=0)
test (_b[ne_op]=0)
test (_b[ne_op]+_b[ne_op_7daymav]+_b[ne_op_14daymav]=0)
test (_b[tt_op]=0)
test (_b[tt_op]+_b[tt_op_7daymav]+_b[tt_op_14daymav]=0)
test (_b[rrr6_op]=0)
test (_b[rrr6_op]+_b[rrr6_op_7daymav]+_b[rrr6_op_14daymav]=0)
test (_b[sunshine_op]=0)
test (_b[sunshine_op]+_b[sunshine_op_7daymav]+_b[sunshine_op_14daymav]=0)
test (_b[ff_op]+_b[ne_op]+_b[tt_op]+_b[rrr6_op]+_b[sunshine_op]=0)
test (_b[ff_op]+_b[tt_op]=0)
by month, sort : regress lnr_aex_lpx_w  lnlp1 lnlp2 lnlp3 lnlp4 lnlp5 lnlpsq1
lnlpsq2 lnlpsq3 lnlpsq4 lnlpsq5 ff_dy ff_dy_7daymav ff_dy_14daymav ne_dy
ne_dy_7daymav ne_dy_14daymav tt_dy tt_dy_7daymav tt_dy_14daymav rrr6_dy
rrr6_dy_7daymav rrr6_dy_14daymav sunshine_dy sunshine_dy_7daymav
sunshine_dy_14daymav  monday tuesday thursday friday  holiday fullmn
newmn, vce(cluster year)
by month, sort : regress lnr_aex_oppx_w lnop1 lnop2 lnop3 lnop4 lnop5 lnopsq1
lnopsq2  lnopsq3 lnopsq4 lnopsq5 ff_op ff_op_7daymav ff_op_14daymav ne_op
ne_op_7daymav ne_op_14daymav tt_op tt_op_7daymav tt_op_14daymav rrr6_op
rrr6_op_7daymav rrr6_op_14daymav sunshine_op sunshine_op_7daymav
sunshine_op_14daymav  monday tuesday thursday friday holiday fullmn newmn,
vce(cluster year)
by month, sort : regress nlnlp nlnlp1 nlnlp2 nlnlp3 nlnlp4 nlnlp5 nlnlp1_sq
nlnlp2_sq nlnlp3_sq nlnlp4_sq nlnlp5_sq ff_dy ff_dy_7daymav ff_dy_14daymav
ne_dy ne_dy_7daymav ne_dy_14daymav tt_dy tt_dy_7daymav tt_dy_14daymav
rrr6_dy rrr6_dy_7daymav rrr6_dy_14daymav sunshine_dy
sunshine_dy_7daymav sunshine_dy_14daymav  monday tuesday thursday friday
holiday fullmn newmn, vce(cluster year)
by month, sort : regress nlnop nlnop1 nlnop2 nlnop3 nlnop4 nlnop5 nlnop1_sq
nlnop2_sq nlnop3_sq nlnop4_sq nlnop5_sq ff_op ff_op_7daymav ff_op_14daymav
ne_op ne_op_7daymav ne_op_14daymav tt_op tt_op_7daymav tt_op_14daymav
rrr6_op rrr6_op_7daymav rrr6_op_14daymav sunshine_op sunshine_op_7daymav
sunshine_op_14daymav  monday tuesday thursday friday holiday fullmn newmn,
vce(cluster year)
```

A.2 Stata Code FTSEMIB

```
import excel "/Users/Mirko/Desktop/Erasmus University/Thesis - Behavioural
Economics/Data_Mirko_Ravasi.xlsx", sheet("FTSEMIB") firstrow case(lower)
rename ap d_2005
rename aq d_2006
rename ar d_2007
rename as d_2008
rename at d_2009
rename au d_2010
rename av d_2011
rename aw d_2012
rename ax d_2013
rename ay d_2014
rename az d_2015
winsor2 lnr_ftsemib_lpx lnr_ftsemib_lpx_sq lnr_ftsemib_oppx
lnr_ftsemib_oppx_sq s2t_lpx s2t_oppx, cuts(1 99)
gen lnlp1= lnr_ftsemib_lpx_w[_n-1]
gen lnlp2= lnr_ftsemib_lpx_w[_n-2]
gen lnlp3= lnr_ftsemib_lpx_w[_n-3]
gen lnlp4= lnr_ftsemib_lpx_w[_n-4]
gen lnlp5= lnr_ftsemib_lpx_w[_n-5]
gen lnlpsq1= lnr_ftsemib_lpx_sq_w[_n-1]
gen lnlpsq2= lnr_ftsemib_lpx_sq_w[_n-2]
gen lnlpsq3= lnr_ftsemib_lpx_sq_w[_n-3]
gen lnlpsq4= lnr_ftsemib_lpx_sq_w[_n-4]
gen lnlpsq5= lnr_ftsemib_lpx_sq_w[_n-5]
gen lnop1= lnr_ftsemib_oppx_w[_n-1]
gen lnop2= lnr_ftsemib_oppx_w[_n-2]
gen lnop3= lnr_ftsemib_oppx_w[_n-3]
gen lnop4= lnr_ftsemib_oppx_w[_n-4]
gen lnop5= lnr_ftsemib_oppx_w[_n-5]
gen lnopsq1= lnr_ftsemib_oppx_sq_w[_n-1]
gen lnopsq2= lnr_ftsemib_oppx_sq_w[_n-2]
gen lnopsq3= lnr_ftsemib_oppx_sq_w[_n-3]
gen lnopsq4= lnr_ftsemib_oppx_sq_w[_n-4]
gen lnopsq5= lnr_ftsemib_oppx_sq_w[_n-5]
gen nlnlp= lnr_ftsemib_lpx_w/(s2t_lpx_w^(1/2))
gen nlnlp1= nlnlp[_n-1]
gen nlnlp2= nlnlp[_n-2]
gen nlnlp3= nlnlp[_n-3]
gen nlnlp4= nlnlp[_n-4]
gen nlnlp5= nlnlp[_n-5]
gen nlnlp_sq=nlnlp^2
gen nlnlp1_sq=nlnlp1^2
gen nlnlp2_sq=nlnlp2^2
gen nlnlp3_sq=nlnlp3^2
```

```
gen nlnlp4_sq=nlnlp4^2
gen nlnlp5_sq=nlnlp5^2
gen nlnop=  lnr_ftsemib_oppx/( s2t_oppx_w^(1/2))
gen nlnop1= nlnop[_n-1]
gen nlnop2= nlnop[_n-2]
gen nlnop3= nlnop[_n-3]
gen nlnop4= nlnop[_n-4]
gen nlnop5= nlnop[_n-5]
gen nlnop_sq=nlnop^2
gen nlnop1_sq=nlnop1^2
gen nlnop2_sq=nlnop2^2
gen nlnop3_sq=nlnop3^2
gen nlnop4_sq=nlnop4^2
gen nlnop5_sq=nlnop5^2
gen  ff_op1= ff_op[_n-1]
gen  ff_op2= ff_op[_n-2]
gen  ff_op3= ff_op[_n-3]
gen  ff_op4= ff_op[_n-4]
gen  ff_op5= ff_op[_n-5]
gen  ff_op6= ff_op[_n-6]
gen  ff_op7= ff_op[_n-7]
gen  ff_op8= ff_op[_n-8]
gen  ff_op9= ff_op[_n-9]
gen  ff_op10= ff_op[_n-10]
gen  ff_op11= ff_op[_n-11]
gen  ff_op12= ff_op[_n-12]
gen  ff_op13= ff_op[_n-13]
gen  ff_op14= ff_op[_n-14]
gen ff_op_7daymav=[(ff_op1+ff_op2+ff_op3+ff_op4+ff_op5+ff_op6+ff_op7)/7]
gen
ff_op_14daymav=[(ff_op1+ff_op2+ff_op3+ff_op4+ff_op5+ff_op6+ff_op7+ff_op8+f
f_op9+ff_op10+ff_op11+ff_op12+ff_op13+ff_op14)/14]
gen  ne_op1= ne_op[_n-1]
gen  ne_op2= ne_op[_n-2]
gen  ne_op3= ne_op[_n-3]
gen  ne_op4= ne_op[_n-4]
gen  ne_op5= ne_op[_n-5]
gen  ne_op6= ne_op[_n-6]
gen  ne_op7= ne_op[_n-7]
gen  ne_op8= ne_op[_n-8]
gen  ne_op9= ne_op[_n-9]
gen  ne_op10= ne_op[_n-10]
gen  ne_op11= ne_op[_n-11]
gen  ne_op12= ne_op[_n-12]
gen  ne_op13= ne_op[_n-13]
gen  ne_op14= ne_op[_n-14]
gen
ne_op_7daymav=[(ne_op1+ne_op2+ne_op3+ne_op4+ne_op5+ne_op6+ne_op7)/7]
gen
```

```
ne_op_14daymav=[(ne_op1+ne_op2+ne_op3+ne_op4+ne_op5+ne_op6+ne_op7+n
e_op8+ne_op9+ne_op10+ne_op11+ne_op12+ne_op13+ne_op14)/14]
gen  tt_op1= tt_op[_n-1]
gen  tt_op2= tt_op[_n-2]
gen  tt_op3= tt_op[_n-3]
gen  tt_op4= tt_op[_n-4]
gen  tt_op5= tt_op[_n-5]
gen  tt_op6= tt_op[_n-6]
gen  tt_op7= tt_op[_n-7]
gen  tt_op8= tt_op[_n-8]
gen  tt_op9= tt_op[_n-9]
gen  tt_op10= tt_op[_n-10]
gen  tt_op11= tt_op[_n-11]
gen  tt_op12= tt_op[_n-12]
gen  tt_op13= tt_op[_n-13]
gen  tt_op14= tt_op[_n-14]
gen tt_op_7daymav=[(tt_op1+tt_op2+tt_op3+tt_op4+tt_op5+tt_op6+tt_op7)/7]
gen
tt_op_14daymav=[(tt_op1+tt_op2+tt_op3+tt_op4+tt_op5+tt_op6+tt_op7+tt_op8+tt
_op9+tt_op10+tt_op11+tt_op12+tt_op13+tt_op14)/14]
gen  rrr6_op1= rrr6_op[_n-1]
gen  rrr6_op2= rrr6_op[_n-2]
gen  rrr6_op3= rrr6_op[_n-3]
gen  rrr6_op4= rrr6_op[_n-4]
gen  rrr6_op5= rrr6_op[_n-5]
gen  rrr6_op6= rrr6_op[_n-6]
gen  rrr6_op7= rrr6_op[_n-7]
gen  rrr6_op8= rrr6_op[_n-8]
gen  rrr6_op9= rrr6_op[_n-9]
gen  rrr6_op10= rrr6_op[_n-10]
gen  rrr6_op11= rrr6_op[_n-11]
gen  rrr6_op12= rrr6_op[_n-12]
gen  rrr6_op13= rrr6_op[_n-13]
gen  rrr6_op14= rrr6_op[_n-14]
gen
rrr6_op_7daymav=[(rrr6_op1+rrr6_op2+rrr6_op3+rrr6_op4+rrr6_op5+rrr6_op6+rr
r6_op7)/7]
gen
rrr6_op_14daymav=[(rrr6_op1+rrr6_op2+rrr6_op3+rrr6_op4+rrr6_op5+rrr6_op6+
rrr6_op7+rrr6_op8+rrr6_op9+rrr6_op10+rrr6_op11+rrr6_op12+rrr6_op13+rrr6_op
14)/14]
gen  sunshine_op1= sunshine_op[_n-1]
gen  sunshine_op2= sunshine_op[_n-2]
gen  sunshine_op3= sunshine_op[_n-3]
gen  sunshine_op4= sunshine_op[_n-4]
gen  sunshine_op5= sunshine_op[_n-5]
gen  sunshine_op6= sunshine_op[_n-6]
gen  sunshine_op7= sunshine_op[_n-7]
gen  sunshine_op8= sunshine_op[_n-8]
```

```
gen  sunshine_op9= sunshine_op[_n-9]
gen  sunshine_op10= sunshine_op[_n-10]
gen  sunshine_op11= sunshine_op[_n-11]
gen  sunshine_op12= sunshine_op[_n-12]
gen  sunshine_op13= sunshine_op[_n-13]
gen  sunshine_op14= sunshine_op[_n-14]
gen
sunshine_op_7daymav=[(sunshine_op1+sunshine_op2+sunshine_op3+sunshine_
op4+sunshine_op5+sunshine_op6+sunshine_op7)/7]
gen
sunshine_op_14daymav=[(sunshine_op1+sunshine_op2+sunshine_op3+sunshine_
op4+sunshine_op5+sunshine_op6+sunshine_op7+sunshine_op8+sunshine_op9+s
unshine_op10+sunshine_op11+sunshine_op12+sunshine_op13+sunshine_op14)/1
4]
gen  ff_dy1= ff_dy[_n-1]
gen  ff_dy2= ff_dy[_n-2]
gen  ff_dy3= ff_dy[_n-3]
gen  ff_dy4= ff_dy[_n-4]
gen  ff_dy5= ff_dy[_n-5]
gen  ff_dy6= ff_dy[_n-6]
gen  ff_dy7= ff_dy[_n-7]
gen  ff_dy8= ff_dy[_n-8]
gen  ff_dy9= ff_dy[_n-9]
gen  ff_dy10= ff_dy[_n-10]
gen  ff_dy11= ff_dy[_n-11]
gen  ff_dy12= ff_dy[_n-12]
gen  ff_dy13= ff_dy[_n-13]
gen  ff_dy14= ff_dy[_n-14]
gen ff_dy_7daymav=[(ff_dy1+ff_dy2+ff_dy3+ff_dy4+ff_dy5+ff_dy6+ff_dy7)/7]
gen
ff_dy_14daymav=[(ff_dy1+ff_dy2+ff_dy3+ff_dy4+ff_dy5+ff_dy6+ff_dy7+ff_dy8+f
f_dy9+ff_dy10+ff_dy11+ff_dy12+ff_dy13+ff_dy14)/14]
gen  ne_dy1= ne_dy[_n-1]
gen  ne_dy2= ne_dy[_n-2]
gen  ne_dy3= ne_dy[_n-3]
gen  ne_dy4= ne_dy[_n-4]
gen  ne_dy5= ne_dy[_n-5]
gen  ne_dy6= ne_dy[_n-6]
gen  ne_dy7= ne_dy[_n-7]
gen  ne_dy8= ne_dy[_n-8]
gen  ne_dy9= ne_dy[_n-9]
gen  ne_dy10= ne_dy[_n-10]
gen  ne_dy11= ne_dy[_n-11]
gen  ne_dy12= ne_dy[_n-12]
gen  ne_dy13= ne_dy[_n-13]
gen  ne_dy14= ne_dy[_n-14]
gen
ne_dy_7daymav=[(ne_dy1+ne_dy2+ne_dy3+ne_dy4+ne_dy5+ne_dy6+ne_dy7)/7]
gen
```

```
ne_dy_14daymav=[(ne_dy1+ne_dy2+ne_dy3+ne_dy4+ne_dy5+ne_dy6+ne_dy7+n
e_dy8+ne_dy9+ne_dy10+ne_dy11+ne_dy12+ne_dy13+ne_dy14)/14]

gen  tt_dy1= tt_dy[_n-1]
gen  tt_dy2= tt_dy[_n-2]
gen  tt_dy3= tt_dy[_n-3]
gen  tt_dy4= tt_dy[_n-4]
gen  tt_dy5= tt_dy[_n-5]
gen  tt_dy6= tt_dy[_n-6]
gen  tt_dy7= tt_dy[_n-7]
gen  tt_dy8= tt_dy[_n-8]
gen  tt_dy9= tt_dy[_n-9]
gen  tt_dy10= tt_dy[_n-10]
gen  tt_dy11= tt_dy[_n-11]
gen  tt_dy12= tt_dy[_n-12]
gen  tt_dy13= tt_dy[_n-13]
gen  tt_dy14= tt_dy[_n-14]
gen tt_dy_7daymav=[(tt_dy1+tt_dy2+tt_dy3+tt_dy4+tt_dy5+tt_dy6+tt_dy7)/7]
gen
tt_dy_14daymav=[(tt_dy1+tt_dy2+tt_dy3+tt_dy4+tt_dy5+tt_dy6+tt_dy7+tt_dy8+t
t_dy9+tt_dy10+tt_dy11+tt_dy12+tt_dy13+tt_dy14)/14]
gen  rrr6_dy1= rrr6_dy[_n-1]
gen  rrr6_dy2= rrr6_dy[_n-2]
gen  rrr6_dy3= rrr6_dy[_n-3]
gen  rrr6_dy4= rrr6_dy[_n-4]
gen  rrr6_dy5= rrr6_dy[_n-5]
gen  rrr6_dy6= rrr6_dy[_n-6]
gen  rrr6_dy7= rrr6_dy[_n-7]
gen  rrr6_dy8= rrr6_dy[_n-8]
gen  rrr6_dy9= rrr6_dy[_n-9]
gen  rrr6_dy10= rrr6_dy[_n-10]
gen  rrr6_dy11= rrr6_dy[_n-11]
gen  rrr6_dy12= rrr6_dy[_n-12]
gen  rrr6_dy13= rrr6_dy[_n-13]
gen  rrr6_dy14= rrr6_dy[_n-14]
gen
rrr6_dy_7daymav=[(rrr6_dy1+rrr6_dy2+rrr6_dy3+rrr6_dy4+rrr6_dy5+rrr6_dy6+r
rr6_dy7)/7]
gen
rrr6_dy_14daymav=[(rrr6_dy1+rrr6_dy2+rrr6_dy3+rrr6_dy4+rrr6_dy5+rrr6_dy6+
rrr6_dy7+rrr6_dy8+rrr6_dy9+rrr6_dy10+rrr6_dy11+rrr6_dy12+rrr6_dy13+rrr6_dy
14)/14]
rename sunshine_lp sunshine_dy
gen  sunshine_dy1= sunshine_dy[_n-1]
gen  sunshine_dy2= sunshine_dy[_n-2]
gen  sunshine_dy3= sunshine_dy[_n-3]
gen  sunshine_dy4= sunshine_dy[_n-4]
gen  sunshine_dy5= sunshine_dy[_n-5]
gen  sunshine_dy6= sunshine_dy[_n-6]
```

```
gen  sunshine_dy7= sunshine_dy[_n-7]
gen  sunshine_dy8= sunshine_dy[_n-8]
gen  sunshine_dy9= sunshine_dy[_n-9]
gen  sunshine_dy10= sunshine_dy[_n-10]
gen  sunshine_dy11= sunshine_dy[_n-11]
gen  sunshine_dy12= sunshine_dy[_n-12]
gen  sunshine_dy13= sunshine_dy[_n-13]
gen  sunshine_dy14= sunshine_dy[_n-14]
gen
sunshine_dy_7daymav=[(sunshine_dy1+sunshine_dy2+sunshine_dy3+sunshine_
dy4+sunshine_dy5+sunshine_dy6+sunshine_dy7)/7]
gen
sunshine_dy_14daymav=[(sunshine_dy1+sunshine_dy2+sunshine_dy3+sunshine
_dy4+sunshine_dy5+sunshine_dy6+sunshine_dy7+sunshine_dy8+sunshine_dy9+
sunshine_dy10+sunshine_dy11+sunshine_dy12+sunshine_dy13+sunshine_dy14)/
14]
summarize  lnr_ftsemib_lpx_w-lnr_ftsemib_oppx_sq_w, format
summarize ff_op-sunshine_op,format
summarize ff_dy-sunshine_dy, format
histogram lnr_ftsemib_lpx_w, normal scheme(sj)
(bin=34, start=-.09590334, width=.00577018)
histogram lnr_ftsemib_oppx_w, normal scheme(sj)
(bin=34, start=-.12015719, width=.0062307)
regress  lnr_ftsemib_lpx_w  lnlp1 lnlp2 lnlp3 lnlp4 lnlp5 lnlpsq1 lnlpsq2 lnlpsq3
lnlpsq4 lnlpsq5 ff_dy ff_dy_7daymav ff_dy_14daymav ne_dy ne_dy_7daymav
ne_dy_14daymav tt_dy tt_dy_7daymav tt_dy_14daymav rrr6_dy
rrr6_dy_7daymav rrr6_dy_14daymav sunshine_dy sunshine_dy_7daymav
sunshine_dy_14daymav  monday tuesday thursday friday january february april
may june july august september october november december holiday fullmn
newmn
estat hettest
estat ovtest
regress  lnr_ftsemib_lpx_w  lnlp1 lnlp2 lnlp3 lnlp4 lnlp5 lnlpsq1 lnlpsq2 lnlpsq3
lnlpsq4 lnlpsq5 ff_dy ff_dy_7daymav ff_dy_14daymav ne_dy ne_dy_7daymav
ne_dy_14daymav tt_dy tt_dy_7daymav tt_dy_14daymav rrr6_dy
rrr6_dy_7daymav rrr6_dy_14daymav sunshine_dy sunshine_dy_7daymav
sunshine_dy_14daymav  monday tuesday thursday friday january february april
may june july august september october november december holiday fullmn
newmn, vce(cluster month)
test (_b[ff_dy]=0)
test (_b[ff_dy]+_b[ff_dy_7daymav]+_b[ff_dy_14daymav]=0)
test (_b[ne_dy]=0)
test (_b[ne_dy]+_b[ne_dy_7daymav]+_b[ne_dy_14daymav]=0)
test (_b[tt_dy]=0)
test (_b[tt_dy]+_b[tt_dy_7daymav]+_b[tt_dy_14daymav]=0)
test (_b[rrr6_dy]=0)
test (_b[rrr6_dy]+_b[rrr6_dy_7daymav]+_b[rrr6_dy_14daymav]=0)
test (_b[sunshine_dy]=0)
test (_b[sunshine_dy]+_b[sunshine_dy_7daymav]+_b[sunshine_dy_14daymav]=0)
```

```
test (_b[ff_dy]+_b[ne_dy]+_b[tt_dy]+_b[rrr6_dy]+_b[sunshine_dy]=0)
test (_b[ff_dy]+_b[tt_dy]=0)
regress  lnr_ftsemib_oppx_w lnop1 lnop2 lnop3 lnop4 lnop5 lnopsq1 lnopsq2
lnopsq3 lnopsq4 lnopsq5 ff_op ff_op_7daymav ff_op_14daymav ne_op
ne_op_7daymav ne_op_14daymav tt_op tt_op_7daymav tt_op_14daymav rrr6_op
rrr6_op_7daymav rrr6_op_14daymav sunshine_op sunshine_op_7daymav
sunshine_op_14daymav  monday tuesday thursday friday january february april
may june july august september october november december holiday fullmn
newmn
estat hettest
estat ovtest
regress  lnr_ftsemib_oppx_w lnop1 lnop2 lnop3 lnop4 lnop5 lnopsq1 lnopsq2
lnopsq3 lnopsq4 lnopsq5 ff_op ff_op_7daymav ff_op_14daymav ne_op
ne_op_7daymav ne_op_14daymav tt_op tt_op_7daymav tt_op_14daymav rrr6_op
rrr6_op_7daymav rrr6_op_14daymav sunshine_op sunshine_op_7daymav
sunshine_op_14daymav  monday tuesday thursday friday january february april
may june july august september october november december holiday fullmn
newmn, vce(cluster month)
test (_b[ff_op]=0)
test (_b[ff_op]+_b[ff_op_7daymav]+_b[ff_op_14daymav]=0)
test (_b[ne_op]=0)
test (_b[ne_op]+_b[ne_op_7daymav]+_b[ne_op_14daymav]=0)
test (_b[tt_op]=0)
test (_b[tt_op]+_b[tt_op_7daymav]+_b[tt_op_14daymav]=0)
test (_b[rrr6_op]=0)
test (_b[rrr6_op]+_b[rrr6_op_7daymav]+_b[rrr6_op_14daymav]=0)
test (_b[sunshine_op]=0)
test (_b[sunshine_op]+_b[sunshine_op_7daymav]+_b[sunshine_op_14daymav]=0)
test (_b[ff_op]+_b[ne_op]+_b[tt_op]+_b[rrr6_op]+_b[sunshine_op]=0)
test (_b[ff_op]+_b[tt_op]=0)
regress  nlnlp nlnlp1 nlnlp2 nlnlp3 nlnlp4 nlnlp5 nlnlp1_sq nlnlp2_sq nlnlp3_sq
nlnlp4_sq nlnlp5_sq ff_dy ff_dy_7daymav ff_dy_14daymav ne_dy
ne_dy_7daymav ne_dy_14daymav tt_dy tt_dy_7daymav tt_dy_14daymav rrr6_dy
rrr6_dy_7daymav rrr6_dy_14daymav sunshine_dy sunshine_dy_7daymav
sunshine_dy_14daymav  monday tuesday wednesday thursday friday january
february april may june july august september october november december
holiday fullmn newmn, vce(cluster month)
test (_b[ff_dy]=0)
test (_b[ff_dy]+_b[ff_dy_7daymav]+_b[ff_dy_14daymav]=0)
test (_b[ne_dy]=0)
test (_b[ne_dy]+_b[ne_dy_7daymav]+_b[ne_dy_14daymav]=0)
test (_b[tt_dy]=0)
test (_b[tt_dy]+_b[tt_dy_7daymav]+_b[tt_dy_14daymav]=0)
test (_b[rrr6_dy]=0)
test (_b[rrr6_dy]+_b[rrr6_dy_7daymav]+_b[rrr6_dy_14daymav]=0)
test (_b[sunshine_dy]=0)
test (_b[sunshine_dy]+_b[sunshine_dy_7daymav]+_b[sunshine_dy_14daymav]=0)
test (_b[ff_dy]+_b[ne_dy]+_b[tt_dy]+_b[rrr6_dy]+_b[sunshine_dy]=0)
test (_b[ff_dy]+_b[tt_dy]=0)
```

```
regress  nlnop nlnop1 nlnop2 nlnop3 nlnop4 nlnop5 nlnop1_sq nlnop2_sq
nlnop3_sq nlnop4_sq nlnop5_sq ff_op ff_op_7daymav ff_op_14daymav ne_op
ne_op_7daymav ne_op_14daymav tt_op tt_op_7daymav tt_op_14daymav rrr6_op
rrr6_op_7daymav rrr6_op_14daymav sunshine_op sunshine_op_7daymav
sunshine_op_14daymav  monday tuesday wednesday thursday friday january
february april may june july august september october november december
holiday fullmn newmn, vce(cluster month)
test (_b[ff_op]=0)
test (_b[ff_op]+_b[ff_op_7daymav]+_b[ff_op_14daymav]=0)
test (_b[ne_op]=0)
test (_b[ne_op]+_b[ne_op_7daymav]+_b[ne_op_14daymav]=0)
test (_b[tt_op]=0)
test (_b[tt_op]+_b[tt_op_7daymav]+_b[tt_op_14daymav]=0)
test (_b[rrr6_op]=0)
test (_b[rrr6_op]+_b[rrr6_op_7daymav]+_b[rrr6_op_14daymav]=0)
test (_b[sunshine_op]=0)
test (_b[sunshine_op]+_b[sunshine_op_7daymav]+_b[sunshine_op_14daymav]=0)
test (_b[ff_op]+_b[ne_op]+_b[tt_op]+_b[rrr6_op]+_b[sunshine_op]=0)
test (_b[ff_op]+_b[tt_op]=0)
by month, sort : regress lnr_ftsemib_lpx_w  lnlp1 lnlp2 lnlp3 lnlp4 lnlp5 lnlpsq1
lnlpsq2 lnlpsq3 lnlpsq4 lnlpsq5 ff_dy ff_dy_7daymav ff_dy_14daymav ne_dy
ne_dy_7daymav ne_dy_14daymav tt_dy tt_dy_7daymav tt_dy_14daymav rrr6_dy
rrr6_dy_7daymav rrr6_dy_14daymav sunshine_dy sunshine_dy_7daymav
sunshine_dy_14daymav  monday tuesday thursday friday  holiday fullmn
newmn, vce(cluster year)
by month, sort : regress lnr_ftsemib_oppx_w lnop1 lnop2 lnop3 lnop4 lnop5
lnopsq1 lnopsq2  lnopsq3 lnopsq4 lnopsq5 ff_op ff_op_7daymav ff_op_14daymav
ne_op ne_op_7daymav ne_op_14daymav tt_op tt_op_7daymav tt_op_14daymav
rrr6_op rrr6_op_7daymav rrr6_op_14daymav sunshine_op sunshine_op_7daymav
sunshine_op_14daymav  monday tuesday thursday friday holiday fullmn newmn,
vce(cluster year)
by month, sort : regress nlnlp nlnlp1 nlnlp2 nlnlp3 nlnlp4 nlnlp5 nlnlp1_sq
nlnlp2_sq nlnlp3_sq nlnlp4_sq nlnlp5_sq ff_dy ff_dy_7daymav ff_dy_14daymav
ne_dy ne_dy_7daymav ne_dy_14daymav tt_dy tt_dy_7daymav tt_dy_14daymav
rrr6_dy rrr6_dy_7daymav rrr6_dy_14daymav sunshine_dy
sunshine_dy_7daymav sunshine_dy_14daymav  monday tuesday thursday friday
holiday fullmn newmn, vce(cluster year)
by month, sort : regress nlnop nlnop1 nlnop2 nlnop3 nlnop4 nlnop5 nlnop1_sq
nlnop2_sq nlnop3_sq nlnop4_sq nlnop5_sq ff_op ff_op_7daymav ff_op_14daymav
ne_op ne_op_7daymav ne_op_14daymav tt_op tt_op_7daymav tt_op_14daymav
rrr6_op rrr6_op_7daymav rrr6_op_14daymav sunshine_op sunshine_op_7daymav
sunshine_op_14daymav  monday tuesday thursday friday holiday fullmn newmn,
vce(cluster year)
```