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Another Look at Calendar Anomalies

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Abstract

Calendar anomalies interest researchers in the finance field nearly a century now. In a 27 years perspective reaching 2017, we employ daily S&P500 data in a context of both aggregate and sector analysis to examine a possible focus of abnormalities on specific constituents of the market. Nonlinear models of GARCH and EGARCH are employed in this spirit. The findings reveal that day-of-the-week effects are present in all sectors, resulting to the conclusion that they are part of a wide phenomenon affecting the whole market structure. Moreover, a rolling regression approach is followed to test for sample selection bias. The presence of seasonality is indeed a small proportion of the total sample period. Four factors, namely recession, uncertainty, trading volume and bearish sentiment are lastly examined for bonding to the presence of daily structures through the intervention of a logit setup. A cross-factor comparison emerges the interactions between recession and uncertainty with the presence of significant anomalies as the most powerful ones. However, trading volume is doubted to experience an actual connection.

Keywords: day-of-the-week effect, GARCH, calendar anomalies, S&P500 Index, sectors, rolling regression, logit

To my family

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[1] www.spdji.com / www.djindexes.com / www.spglobal.com

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Chapter 1

Introduction

In recent years, there has been an extensive amount of work on the examination of anomalies in the stock markets. The first question that could cross one's mind is: What is actually an anomaly? In reply to this question, we would declare that it is just an abnormality in the stock market. It is the incidence when under a given set of assumptions, the actual results do not follow the expected results and there is no prevailing theory to explain the pattern. There is no justification for its presence from any of the existing asset pricing models like the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT). Essentially, such distortions from normality stimulate the interest of many economists as their existence challenges a cornerstone of modern economic theory - the renowned Efficient Market Hypothesis.

Efficient Market Hypothesis (EMH) is one of the most-discussed topics in the finance literature. It was first proposed by Samuelson [1965] and Fama [1965]. This hypothesis denotes that the market is efficient in the sense that all public information spreads rapidly and accurately in the market, and as a result, it is reflected immediately in the stock prices. Therefore, it is impossible for investors to either buy undervalued stocks or sell overvalued stocks. Instead, all securities are traded for their intrinsic or fair value and there is no opportunity for investors to outperform the market. The process of stock prices follows a so-called "random walk". This means that the process is characterized by a complete randomness and no predictions of future values can be formed. Many economists since then shared the same belief. However, due to its excessive assumptions, many others doubted its correctness in a "real world" market, in light of evidence of various types of abnormalities.

There is an old joke illustrating the situation. There are two economists walking down the street when they suddenly notice a $100 bill on the ground. The first one says: "Look there is a $100 bill!". The second economist then replies: "Do not bother to pick it up. It must be a counterfeit. Markets are efficient, so if it were a real $100 bill, someone would have come by and picked it up already."

Indeed, whichever pattern is observed, it is expected not to retain its structure forever. It typically lasts only for a short time horizon[1]. Gradually, more and more market participants are observing the abnormal behavior and designing their strategies upon that. This increased awareness is the cause that shortens the life of the stock market anomaly. As Marquering et al. [2006] noted, once a pattern gets published, it starts to lose its strength and eventually it disappears if it is the outcome of data snooping (see above). It is truly remarkable that the timing of disappearance or reappearance of the anomalies often coincides with the timing of the subjacent scientific publications.

This study focuses on calendar anomalies field - the most documented one out of the total group of anomalies. Their name betrays that these irregularities are seasonal tendencies related to the calendar. The literature is enriched with a highly diverse range of different branches of them, but the most popular of all are the day-of-the-week, the turn-of-the-month, the month-of-the-year effects (especially the January effect) along with the holiday and Halloween effects. We will introduce the remaining four anomalies in short here, letting the day-of-the-week effect to be presented immediately afterward with greater details. The turn-of-the-month effect refers to the tendency of stock prices to rise on the last trading day of a month and the following three trading days of the next month[2]. The famous January effect requires higher daily returns in this month of the year relative to the others[3]. Holiday effect shows significantly higher returns on days prior to public holidays[4]. Halloween effect or "Sell in May and go away" effect refers to the anomaly where stock returns are lower during summer months (May - October) comparing to winter months (November - April)[5].

The day-of-the-week effect is named after the phenomenon where some days of the week exhibit systematically higher or lower returns compared to the others. Of particular interest to researchers has been the traditional weekend effect according to which Monday returns are the lowest among the other days of the week or even significantly negative in some cases (Monday effect), while the Friday returns are positive and the highest ones (Friday effect).

There is an interesting query then that arises. According to these anomalies, can someone make profits? Such a contingency would seem to oppose to EMH. The latter argues that no investing group has the ability to design profitable trading strategies that could produce excessive returns for long pe-

[1]For a detailed description of the evolution of the weekend effect in the US stock market, see Olson et al. [2015].

[2]See for example Jacobs and Levy [1988] and Ziemba [1991].

[3]See Rozeff and Kinney [1976] and Haug and Hirschey [2006] for the US market and Asteriou and Kavetsos [2006] for 8 transition economies.

[4]See Lakonishok and Smidt [1988] and Vergin and McGinnis [1999].

[5]See for example Bouman and Jacobsen [2002] and E. D. Maberly, Pierce, et al. [2004].

riods. There are indeed thousands of investors that are fascinated of these anomalies and could do whatever on the hunt for even a percent of extra performance. However, most analyses exclude real-world facts like transaction costs, commissions and taxes. Once these factors are accounted for, net gains tend to be zero and only short-time benefits can be attained. Nevertheless, it is a risky move to mechanically follow such patterns, as they are unpredictable to some extent. They appear in the markets, relax, disappear and reappear with no warning signs. As French [1980] noted, the only thing that investors can do is to rearrange their positions. For example, they should shift their selling positions scheduled for the start of the week to the preceding Friday and the buying positions planned for the end of the week to the following Monday. While these anomalies are worth exploring, investors should move with great caution and skepticism to avoid nonnegligible losses.

On a fundamental level, there are no particular explanations widely accepted for the day-of-the-week anomalies. Many researchers though have tried to offer potential ones. Measurement errors, bid-ask spreads, settlement procedures, the trading activity of institutional compared to individual investors, the information processing hypothesis, investors' sentiment and other psychological factors, the hypothesis related to the release of information and particularly that of bad news, previous market conditions and spillover effects are among the most documented ones. Many of those have been rejected even from those who first proposed them while others have been argued to partially explain the behavior of stock movements. Still, an integrated survey needs to be made in this field to clarify their actual sources.

Through the years, day-of-the-week effects have been discovered not only in stock market indexes but also in foreign exchange rates, stock options, stock index futures (Yadav and Pope [1992]), in bonds and T-bills (Gibbons and Hess [1981]) both in developed and emerging markets. They have been examined for robustness and correlation with other calendar anomalies. In this spirit, Sullivan et al. [2001] attempted to answer whether calendar anomalies are the outcome of data mining supporting that previous studies had been using the same data set to formulate and test hypotheses. They conclusively found that although nominal *p-values* of individual calendar anomalies were extremely significant, once all universe of calendar anomalies was considered, the anomalies detected lost their strength.

Our contribution to the existing literature is threefold. First, we offer an examination of day-of-the-week effects both in the broad-based S&P500 Index and its 10 sectors in a 27 years perspective. A sector-specified approach has not been extensively followed. We are actually trying to find whether the anomalies found in the broad index have a particular pattern living in specific sectors or whether they are part of a wide phenomenon spreading across the entire market. Second, we test our results for robustness. Are those anomalies focused on specific time periods? Do they follow some trend? These questions are answered through a rolling procession. Third but not least, we are trying

to bond the presence of daily abnormalities to various factors. Is it really more likely to experience them in presence of specific market conditions?

This bachelor thesis is organized in the following manner. First, we review empirical conclusions of other researchers focusing exclusively on the day-of-the-week anomaly. Second, we describe the data set benefiting from the statistics knowledge and compare the findings across different sectors. Then, we provide a theoretical background in the ARCH-family models, rolling regression technique and limited dependent variable models. Finally, we provide some concluding remarks and discuss the findings.

Chapter 2

Literature Review

2.1 A brief journey on paths of daily seasonality

The history of the analysis of day-of-the-week effects traces us back nearly a century. The first theory prevailing in the researchers papers was the constancy of returns across all days of the week. The pioneering work of Fields [1934] came as a firework to disrupt the tranquility of the scientists. Examining the period of 1915 - 1930 for the DJIA index, he tracked a rise (fall) in stock prices before (after) the weekend. Many years later, Fama [1965] discovered a 20% increase in volatility on Mondays relative to the other days, which contradicted the previous belief and offered support to the work of Fields [1934]. The first studies following were occupied especially with the weekend effect and Monday-Friday relationship.

In the 1970s and the 1980s, a tremendous stream of literature was dedicated to the day-of-the-week effects. Cross [1973] using S&P500 Index data from 1953 to 1970 found surprisingly negative returns for Mondays, a decade after the findings of Fama [1965]. The mean returns for Fridays were above the mean returns for Mondays, collecting evidence of a weekend effect. In his attempt to test if the stock returns are generated through a calendar time hypothesis or a trading time hypothesis[1], French [1980] found same results. He extended the previous study's data set to 7 years but essentially nothing changed.

Gibbons and Hess [1981] examined the Monday effect in greater detail trying to find what causes it. They utilized daily prices of the S&P500 Index and the value- and equal-weighted portfolios constructed by the CRSP

[1]The calendar time hypothesis requires expected Monday returns to be three times the expected returns for the other days of the week since, according to the calendar, there are three days between Friday's close and Monday's close.

The trading time hypothesis states that the expected returns should be equal to all days of the week since returns are generated only during trading hours.

covering the period between 1962 through 1978. Their conclusions consist of strong negative mean Monday returns for stocks and below-average returns on Monday for the T-bill market. Measurement errors and different settlement procedures did not provide adequate justification for the observed anomalies. Keim and Stambaugh [1984] continued that work taking into account additionally 55 years. The last trading day proved to show the highest returns again. Their novelty of distinguishing firms with respect to their size gave interesting findings. The small size decile appeared the strongest day-of-the-week effects, while the large one appeared the weakest. Measurement errors and bid-ask spreads did not support their persistence.

Prince [1982] offered another milestone in the journey of exploring anomalies. He decomposed the Monday returns into two components: the first one between the Friday close and the Monday open and the second one between the Monday open and the Monday close, in order to identify if the irregularities are a trading or a non-trading phenomenon. The DJIA data from 1960 to 1964 showed that the Monday effect is caused during the trading hours of Monday. Rogalski [1984] with use of intraday data from 1974 to 1984 obtained different findings. He ascribed the Monday effect to the non-trading time of the weekend. In fact, he linked the anomaly to the January effect, as Monday returns were positive in January nut negative in other months of the year.

Outside the U.S. territory, Jaffe and Westerfield [1985] dealt with the cases of Australia, Canada, Japan and U.K. They studied if the day-of-the-week effects are experienced worldwide or are an exclusive privilege of the United States. Indeed, evidence of the lowest returns on Tuesdays was pointed in the Australian and the Japanese stock markets. Moving to France, Solnik and Bousquet [1990] with data from a forward market, namely Paris Bourse, detected negative Tuesday returns. Settlement procedures were adequately explaining the high Friday returns. In the Asian continent, Choudhry [2000] found significant patterns on volatility, though different in the 7 markets involved.

In the late 1980s, despite the vast majority of literature backing the existence of anomalies, Connolly [1989] proposed that such phenomena actually disappeared after 1975. In the same lines, Andrew Coutts and Hayes [1999] declared that the Monday effect did exist in the UK, but weakened compared to UK stock indexes that had been previously documented. Steeley [2001] also pointed that the weekend effect disappeared in the 1990s for the UK stock market and that it was only vivid when partitioning the returns according to the direction of the market. Likewise, Mehdian and Perry [2001] found that in the 1987-1998 period, Monday returns were not significantly different from returns of the other days of the week for the large-cap indexes of S&P500, DJCOMP and NYSE.

The empirical documentation of proofs for and against the day-of-the-week effects continued to appear. Day-of-the-week effects on volatility were

evident in the paper of H. Berument and Kiymaz [2001] as well. In terms of returns, Monday exhibited the lowest and Wednesday the highest, while in terms of volatility, an increased pattern was observed on Fridays and weaker on Wednesdays. Bad news stood as a causal factor for the Friday's highest volatility being suggested to influence the behavior of investors.

Day-of-the-week effects are less documented for cross-sector data. However, more and more researchers tend to concentrate on various sectors of the broad indices. In the middle of 1980s, Santesmases [1986] faced no day-of-the-week effect. Daily returns of the Madrid stock exchange index and 40 stocks divided into 3 groups (Banks and Investments, Utilities and Industrial stocks) covering 1979-1983 were utilized for this purpose. In contrast, Peña [1995] studying the same stock market more recently, for the years 1986-1993, used daily returns of 7 sectoral portfolios. Among his conclusions were the positive Monday mean returns before the CATS but no daily structure was found after the reform.

In Thailand, Kamath et al. [1998] also experienced day-of-the-week effects with daily prices of the ten sectors of the SET during 1980-1994. Negative Monday returns and positive Friday returns were present for all sectors. The results concluded to be robust across 2 different methodologies followed.

Coutts et al. [2000] investigated the presence of anomalies in the Greek stock market over a ten-year period from 1986 to 1996. Three major industry indexes were considered: Banking, Insurance and Leasing. The results were complicated. Day-of-the-week effects were dominant only in the General and the Banking sector indexes. Monday displayed positive average returns but Tuesday and Wednesday displayed negative ones. In the second subperiod (after 1991), the scenery changed. A weekend effect appeared in the ASE, as a consequence of the institutional changes in 1992.

Lucey [2002] provided useful insights into seasonal anomalies for the Irish stock exchange with its two sector indices: Financials and Industrials. A Wednesday effect appeared in mean returns, contrary to findings elsewhere. He also concluded that variations in the first four moments were stronger in rising than falling markets.

The weekend effect and the "reverse" weekend effect existed in both broad indices of DJIA and NYSE and industry indices, in the study of Brusa et al. [2003] during the 1966-1996 period. The most interesting fact outlined was the similarity of patterns between the broad and industry indices even after sorting the data by month-of-the-year and week-of-the-month. By dividing the sample period into pre- and post-1988, Monday returns changed their patterns, although the similarity between the two groups continued. This indicated that the cause of the daily seasonality is economically based and not industry-specified, in which case only a few sectors of the economy would experience the anomalies.

Kenourgios et al. [2005] also observed a changing pattern in the ASE Index along with five sector indexes: Banking, Insurance, Miscellaneous, FTSE-20

and FTSE-40 pre- and post- 2000. There appeared to be undoubtful evidence for daily seasonality in both return and volatility for all indices pre-2000, which were partly consistent with Coutts et al. [2000]. Leaving the cases of the general and FTSE-40, the remaining indices did not maintain the previous anomalies post-2001, probably due to the Greek entry to the Eurozone and the market reform as a developed. An examination of the differences due to the entry in the Euro-zone was also made by Högholm and Knif [2009], this time for the case of the Finnish stock market. During the pre-euro period, variations in volatility across days of the week were strongly evident in both the broad index and two of the industries examined, originating from the sectors of Consumption Goods and Forestry & Paper. However, in the post-euro period, all 4 industry-specific indices showed seasonality in volatility.

An additional industry-focused study was that of Liu and Li [2010] who used closing prices from top 49 industries in Australia for the 2001-2010 period. They empirically found a reverse Monday effect (positive mean returns) in 15 indices mostly originating from the Materials and Energy sectors. Surprisingly, 6 companies were characterized by the highest mean returns on Mondays across all days of the week. Similar structures in Materials were found by Mbululu and Chipeta [2012], who analyzed the 9 sectors of the JSE market. All sectors did not show day-of-the-week effects with an exception of a Monday effect on the Basic Materials sector.

More recently, Bampinas et al. [2016] focused on the real-estate sector using 20-year data from 1990 through 2010. They found significant Monday effect in 3 national indices and Friday effect in half of the 12 indices examined. But once they were evaluated in a rolling framework, no significant patterns were observed.

A selected set of studies concerning both market indexes and sector-specified ones are presented in the following Table 2.1.

Table 2.1: A selected summary of literature

Author(s)	Data	Methodology	Empirical Findings
Panel A: Daily seasonality in aggregate stock indices			
Jaffe & Westerfield [1985]	Daily returns of stock market indexes of Japan (Nikkei Dow 1970 - 1983), Canada (Toronto Stock Exchange Index 1976 - 1983), Australia (Statex Actuaries Index 1973 - 1982), the U.K. (Financial Times Ordinary Share Index 1950 - 1983) and the U.S. (S&P500 1962 - 1983)	OLS regression analysis	A weekend effect found in all markets and a Tuesday effect in Australia and Japan. Investors' actions in foreign markets were independent of those in the U.S. The Australian pattern was partly explained by the time zone difference with the U.S.
Alexakis & Xanthakis [1995]	A representative stock price index of the Athens Stock Exchange covering the period from January 1985 to February 1994, investigated as a whole and divided into two subperiods 1985 - 1987, 1988 - 1994	EGARCH - M model	Positive returns for all days except Tuesday for the whole period and first sub-period. The second sub-period introduced negative Monday returns along with Tuesdays.
Choudhry [2000]	Daily returns of 7 emerging Asian stock markets from January 1990 to June 1995	GARCH(1,1) model	Significant negative Monday returns for Indonesia, Malaysia and Thailand. Positive Monday effect on volatility for all markets except India. A possible explanation was a spillover from the Japanese stock market but no the settlement procedures.
Cho et al. [2007]	Daily returns of DJIA and S&P500 from 1/1/1970 - 12/31/2004, NASDAQ, Russell2000 and CRSP from 1/1/1988 - 12/31/2004, Nikkei 225 and FTSE 100 from 1/1/1990 - 12/31/2004	OLS regression analysis, Stochastic dominance approach	A Monday effect for most of the indexes. After 1987 weakness of the effect for DJIA and S&P500 but remanence of significance for broader based indices.
Alagidede & Panagiotidis [2009]	Daily closing prices of the DSI index on the GSE covering the period between June 15, 1994 to April 28, 2004	OLS regression analysis, GARCH, EGARCH and TGARCH, rolling window regression	Out of the 3 weekdays that GSE market is open, Friday showed the most significant returns. This daily anomaly vanished within a rolling framework.
Berument & Dogan [2012]	Daily data of 9 US indexes: the equal- and value-weighted NYSE, S&P500, NASDAQ, AMEX and equal-weighted DOW from May 26, 1952 to September 29, 2006	EGARCH-M model	When risk premium was supposed to be constant across the days of the week, highest (lowest) returns were observed on Fridays (Mondays) and a positive risk premium was found along with a leverage effect. Similar results were obtained when risk premium was allowed to differ, but no findings sustained its presence and constancy during the week.

Table 2.1 *(continued)*

Author(s)	Data	Methodology	Empirical Findings
Bush & Stephens [2016]	Daily returns of 5 currency pairs: US dollar, Japanese yen, Great British pound, Canadian dollar and Australian dollar with Euro as base currency, studied in three periods 1999-2004, 2005-2009, 2010-2012	OLS regression analysis	Weak evidence (1/5 currency pairs) of Monday effect in the first two sub-periods. Reappearance of the anomaly after the global economic crisis (3/5)
Zhang et al. [2017]	Daily stock returns of 28 market indices in 25 countries (15 from emerging markets and 13 from developed ones). Data range from 1990 to 2016	GARCH model, rolling sample method, calendar effect performance ratio	Day-of-the-week effects did exist in all markets examined. Robust results across periods. Calendar anomalies did not vanish for 6 indices chosen when they were measured in US dollars.
Panel B: Disappearance of daily anomalies			
Connolly [1989]	Daily returns for the S&P500, the equal- and value-weighted CRSP indexes covering the period between the first trading day in 1963 and the last one in 1983	OLS regression analysis with sample size-adjusted critical F-values and error normality tests, M-distribution free estimators, GARCH(1,1)	The weekend effect was weaker than suspected before and disappeared in the mid-1970s. A correction for heteroskedasticity and autocorrelation weakened the abnormality until the mid-1970s.
Coutts & Hayes [1999]	UK stock market data of FT 30 beginning from June 8, 1979 till December 31, 1994	OLS regression analysis	A weekend effect was present but weaker than was previously documented. Settlement procedures partly explained the pattern.
Steeley [2001]	Daily returns of FTSE100 during April 1991-May 1998	OLS regression analysis	A weekend effect was absent. A combined Monday and Friday effect was found on the bad news data. Stronger evidence of anomaly on announcement-bad news days. Possible explanation was the surprise seasonality.
Mehdian & Perry [2001]	Daily closing prices for 5 major US indices DJCOMP, NYSE, S&P500, NASDAQ, RUSSELL2000 from June 4, 1964 to February 6, except for RUSSELL in which start date is the 1998 January 2nd, 1979	OLS regression analysis, Chow Breakpoint Tests, Recursive Coefficient Estimations	Significant negative average Monday returns were found over the whole sample. The pattern was unstable over the entire period, but stable in two subperiods: pre-1987 and post-1987. Significant reversal of the Monday effect over time for the large-cap stocks.

Table 2.1 *(continued)*

Author(s)	Data	Methodology	Empirical Findings
Panel C: Sectoral focus			
Santesmases [1986]	Daily returns of the Madrid stock exchange index and 40 stocks divided into 3 groups (banks and investments, utilities and industrial stocks) covering January 1979-December 1983	OLS regression analysis (F-statistic)	No day of the week effect detected rather a turn of the year effect.
PeÑa [1995]	Daily returns of the Madrid stock market index (IGBM) and 7 sectorial portfolios during January 1986-March 1993	OLS regression analysis (Ljung-Box, t-stat., F-stat.)	Positive average Monday returns before the CATS but no daily structures after the reform.
Kamath, Chakornpipat & Chatrath [1998]	Daily prices of the Thailand's Stock Exchange (SET) and its ten sector indices for the period January 1980-December 1994	OLS and GARCH(1,1) model	Significant negative Monday returns and positive Friday returns for all 11 indices examined. Robust results across the 2 methods employed.
Coutts , Kaplanidis & Roberts [2000]	Daily data prices of the Athens Stock Exchange general index (ASE) and its 3 major indices: banking, insurance and leasing from October 1986 through August 1996	OLS regression analysis	Day of the week effect in market and banking sector for the whole period and 2nd sub-period (1991-1996). For the 1st one, negative Tuesday and Wednesday average return were observed. Positive January returns for all indices except for insurance and strong evidence for holiday effect.
Lucey [2002]	Daily percentage returns of the Irish stock market index (ISEQ), the corresponding index of total returns (ISEQR) from January 1988 to December 1998 and two sectoral indices: financial (ISEFIN) and industrial (ISEGEN) from February 1989 to December 1998	F, Kruskal-Wallis and Levene tests	Evidence suggested a Wednesday effect in mean and a stronger seasonality in rising markets.
Brusa et al. [2003]	Daily data from 2 market indices DJIA, NYSE, 4 major NYSE industry indices and 20 industry indices from 1966 to 1996	OLS regression analysis	Reverse (traditional) weekend effect in the 2 market indices for the post (pre) - 1988 subperiod. Similar results for the industry indices even when the month of the year and week of the month effects were accounted for.

Table 2.1 *(continued)*

Author(s)	Data	Methodology	Empirical Findings
Kenourgios, Samitas & Papathanasiou [2005]	Closing prices of the Athens Stock Exchange general index for ten years January 1995 to December 2004, and five major indices for the two sub-periods 1995-2000 (banking, insurance, miscellaneous) and 2001-2004 (FTSE-20, FTSE-40)	GARCH(1,1) & modified - GARCH(1,1)	An intense existence of the day of the week effect in returns and both returns and volatility for the whole period and 1st sub-period. Weakness of the anomaly for the 2nd one, except for the general and FTSE-40 indices.
Högholm & Knif [2009]	Daily data from the Finnish OMX Cup stock market index and 4 sector indices with 4 corresponding firms' data: Basic Materials (Huhtamaki), Consumption Goods (Kesko), Forestry and Paper (UPM) and Industrials (Kone) from April 1993 to June 2006	Unconditional: ANOVA F-test, Kruskal-Wallis test, Brown - Forsythe test Conditional: EGARCH model	In the pre-euro period, intraweek patterns in the volatility were found for the market and 2 of the firms' indices. During the post-euro period, such patterns were found in both the mean for 3 series and the variance for all 4 industry indices.
Liu & Li [2010]	Daily closing stock returns of the top 49 Australian companies for the period January 2, 2001-June 30, 2010	t-tests	Largest mean returns on Mondays for 15 companies (mostly in materials and energy sectors). Larger the Monday returns than returns in any other days for 6 companies.
Mbululu & Chipeta [2012]	Daily closing value-weighted index values for 9 sectors of JSE from July 3, 1995 to May 13, 2011	Kolmogorov-Smirnov test	Day-of-the-week effects were absent in all indices, except for the basic materials sector where a Monday effect was present.
Bampinas et al. [2016]	Daily returns of a global, a european and 12 national (european) securitized real estate indices from January 15, 1990 to May 11, 2010	Unconditional: Kruskal-Wallis test for ranks, modified Levene Conditional: GARCH(1,1), GJR-GARCH, EGARCH, rolling window regression	Significant Monday effect for 3 national indices and higher Friday returns for 6 national and the 2 regional indices. Adoption of the rolling regression approach reduced the power of the day-of-the-week effects.

2.2 But why day-of-the-week effects?

A special section of this chapter is focused exclusively on the examination of the sources that have been proposed to lead to the existence of anomalies. It is really puzzling and irritating at the same time when after tones of studies an in-depth conclusion has not been formulated yet. Therefore, it is worth to devote some space for a flashback of the honorable efforts to comprehend their recommended explanations.

The first assumption that appeared is that day-of-the-week effects are caused by measurement errors. This error can bias upwards the Friday's price and downwards the Monday's price, widening the gap between those two. This way, it helps to sustain the negative correlation between them, but it cannot be satisfactory to explain why the Friday-Monday correlation is the highest of the week. Measurement error is caused when stocks have low merchantability and it is more common to companies with low capitalization. These companies are indeed those for which the day-of-the-week effects are found stronger (Lakonishok and Smidt [1988]).

Another possible explanation is the bid-ask spread. Daily stock returns are calculated using closing prices. The closing price reflects the price of the last transaction either it was a sale or a purchase. This price does not show the actual price at which the order of sales and purchases would be balanced but an unreal price. The bid-ask spread is found larger, due to the tendency of prices to close at the ask on Fridays and at the bid on Mondays[2]. However, this explanation has been rejected by many studies so far.

Settlement procedures and clearing delays or the liquidation system of transactions could also have helped create this phenomenon (Gibbons and Hess [1981], Lakonishok and Levi [1982], and Solnik and Bousquet [1990]). As it was pointed, these force investors to be unwilling in certain days of the week to buy at the same price levels as in other days because they do not get the two days of extra credit granted by the weekend. The settlement procedure is referring to the period between the order of the sale or purchase and the final delivery or receiving of the title. The associated effect causes distortions in prices due to the delay since transactions are settled. Here we will present an example to get this clear. Since 1968, the settlement period is set to five business days. Under the assumption that checks clear via the United States Federal Reserve System, an extra business day is required for crediting and debiting by banks. The final settlement will take place 8 business days after the trading for all days except Friday: 5 days for settlement, 2 weekend days and 1 check clearing day. However, Friday requires 10 business days, since an extra weekend is involved. Therefore, buyers should expect to face a higher price on a Friday by the amount of two days interest. Sellers should also demand a higher price since they will be paid 2 days later. Consequently, the equilibrium expected return on Friday should be higher than on other

[2]See Porter [1988] for an analysis of the bid-ask spreads.

weekdays. Analogously, the equilibrium expected return on Monday should be lower. This explanation is still not satisfactory since the day-of-the-week effects exist in different countries with different settlement procedures.

The institutional trading offers the most satisfactory explanation for the day-of-the-week effects (Lakonishok and E. Maberly [1990]). This theory states that individual investors opposed to institutional, trade mostly on Mondays. The propensity of individuals for transactions is the highest on Mondays relative to the other days of the week, while that of institutions is the lowest. Individual investors' ability to process the available information after the trading hours, especially on weekends, leads to the Monday effect. Consequently, Monday is proved to be the day with the lowest trading volume. Sias and Starks [1995] highlighted that the institutional trading activity plays the catalytic role, as institutions are those who transact in markets abroad. As they noted, institutions' trading can explain the shift of the negative returns in the U.S. and the Tuesday's negative returns in certain markets like Japan.

The above explanation is based on the Information Processing Hypothesis. According to Lewellen et al. [1980], an amazing 77% out of six thousands of stockbrokers recommendations, suggests purchases, while only the 23% suggests sales. In the middle of the week, investors prefer to take the advice of the stockbrokers in modeling their strategies due to the lack of valuable time to be self-informed about the market conditions. Then, in the two free days of the weekend, when the market is closed, they can read the news and be satisfactory informed to develop their own moves after reviewing their portfolios on weekends. That is the reason Fridays' positions are mostly purchases, while Mondays' are mostly sales.

The existence of consistently occurring irregularities in conventional economic theory acted as a major benefactor to the configuration of behavioral finance. If the behavior was rational and logical, such violations of the financial theories would definitely not have been present. Perhaps, some psychological factors can affect the trading activity of market participants. Rystrom and Benson [1989] were the pioneers who shed light to this perspective. An end-of-the-week optimism fuels the market, as investors are looking forward to the leisure of forthcoming weekend. Likewise, in the weekend, investors have the chance to proceed with briefings, concern about the market and develop pessimism resulting into Monday, the first working day of the week. Therefore, they forward sales on Mondays and purchases on Fridays concluding to a drop in prices on Mondays and a rise on Fridays.

There is also a belief that some anomalies are linked to the announcement of information either this has microeconomic foundations regarding stock splits, earnings, and mergers and acquisitions or macroeconomic. Companies are said to announce bad news over the weekend in order to endow the market with the appropriate time needed to absorb the shock during the two non-trading days between Friday's activities and Monday's trading. (Lakon-

ishok and E. Maberly [1990], Penman [1987]). On the other hand, good news releases occur immediately. Penman [1987] also marked that the governmental economic executives tend to delay the dissemination of unfavorable macroeconomic news until the closure of the markets on Friday.

Another recommendation from researchers is the previous market conditions. The presence of negative returns in previous meetings and mostly on preceding Friday raises the possibility of negative attributions on the following Monday. In eras of instability and economic downturn, Monday returns are expected to be more negative than in periods of economic rise, specifically in the case when the market experienced a decline in the preceding week, according to the conclusions of Abraham and Ikenberry [1994].

Lastly, there have been studies discussing a possible spillover effect in related markets, indicating that a day-of-the-week effect in one market is caused by day-of-the-week effects in other correlated markets. Since the first examination of day-of-the-week effects was performed in the U.S. market, it was reasonable to test their presence worldwide for receiving a broader picture. Jaffe and Westerfield [1985] studied international markets to see if the anomalies were originated from the U.S., specifically the stock exchanges of Australia, Japan, Canada and the United Kingdom. For the Japanese and Australian exchange, Tuesday returns were found significantly negative and the lowest among all weekdays. The time-zone differences and correlations between the domestic countries and the United States were the possible explanations, neither of them explaining completely the above-mentioned irregularities. Spillover effects can exist through two possible offshoots. The first scenario is the causal relationship between the two involved markets. The second is the share of similar international client list between them. That can release the same behavior characteristics or trading preferences of investors to the markets, which are often responsible for the anomalies. International evidence shows that migration of such effects is doubted to explain the patterns.

Chapter 3

Data & Methodology

3.1 Data description

3.1.1 S&P500 Index and its sectors

This study utilizes return series for the Standard & Poor' s 500, typically abbreviated as the S&P500 Index, together with its 10 out of 11 sectors. The S&P500 is widely regarded as the most representative single gauge of large-cap equities. It is constructed to reflect the picture of the U.S. markets and consequently the whole U.S. economy. There is over USD 7.8 trillion benchmarked to the index, with assets comprising approximately USD 2.2 trillion of this total. The index comprises 500 leading companies (not necessarily the 500 largest) and captures approximately 80% coverage of available market capitalization. The selection of companies to stand as components of S&P500 is managed by a committee which ensures the fulfillment of the following eligibility criteria as quoted in the report of S&P Dow Jones Index Methodology: 1) unadjusted company market capitalization of USD 6.1 billion or more, 2) the ratio of annual dollar value traded to float-adjusted market capitalization should be 1.00 or greater, and the stock should trade a minimum of 250,000 shares in each of the six months leading up to the evaluation date, 3) it must be a U.S. company, 4) public float of at least 50% of the stock, 5) the sum of the most recent four consecutive quarters' earnings should be positive as should the most recent quarter, 6) initial public offerings should be traded on an eligible exchange for at least 12 months before being considered for addition to an index, 7) eligible securities are the common stock of U.S. companies with a primary listing on one of the following U.S. exchanges: NYSE, NASDAQ and Bats. There is always the possibility of deletion for a company from the constituent's list, at times when the above criteria are no longer met. The index calculation and the weighting methodology is complex and not the scope of this study. Thus, a concerned

researcher can address to the following website www.spdji.com for further details.

The S&P500 Index consists of eleven sectors: 1) Consumer Discretionary, 2) Consumer Staples, 3) Energy, 4) Financials, 5) Health Care, 6) Industrials, 7) Information Technology, 8) Real Estate, 9) Materials,10) Telecommunication Services and 11) Utilities, based on the industry taxonomy of the Global Industry Classification Standard (GICS). This categorization enables market participants to identify and analyze companies from a specific perspective breaking down the market into 11 sectors and thus highlighting the sector characteristics of the S&P500 Index. We focus on 10 out of these 11 sectors, excluding the Real Estate sector as it is a brand new sector secluded from Financials post-September 16, 2016 thus the data available are too short. Pie Chart 3.1 below shows the weighting of each sector of the index as of June 30, 2017 [1].

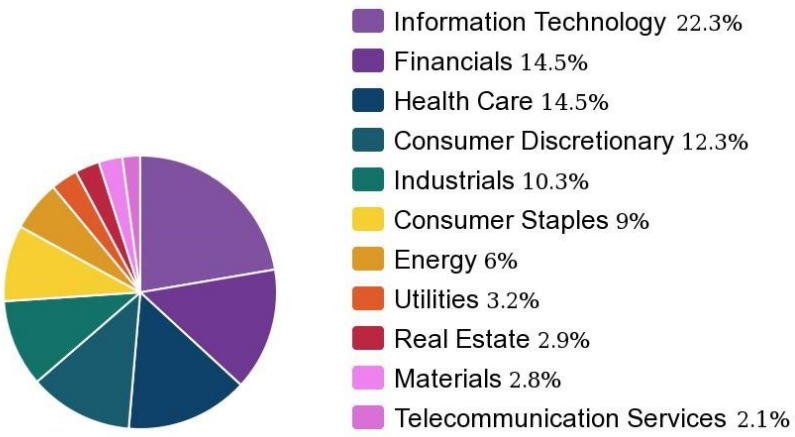

Figure 3.1: The weightings for each sector of the S&P500 Index, as of June 30, 2017, based on GICS sectors.

The most important segment of the S&P500 Index is the Information Technology sector which covers above 22% of the total index's equity. Among the biggest constituents of this sector, are Apple Inc., Microsoft Corp and Facebook Inc A. Financials and Health Care hold the second and third seats, each with a 14.5% weighting. The smallest portion of the index belongs to the Telecommunication Services sector with a weak 2% weighting.

The closing price data for S&P500 and its ten sectors span from September 11, 1989 to January 6, 2017 (provided upon request from the S&P Dow Jones Indices)[2]. The data frequency is daily as the nature of the problem suggests,

[1]The weightings for each sector of the index are rounded to the nearest tenth of a percent; therefore, the aggregate weights for the index may not equal 100%. Source: http://eu.spindices.com/indices/equity/sp-500

[2]Data for the last 10 years can be found on the website http://us.spindices.com.

in order to explore the distortions across the days of the week. This gives us a total of more than 27 years, a long time horizon to actually observe the evolution of potential day-of-the-week effects. The returns for each day, t, is computed as the first logarithmic differences using the formula:

$$R_t = log(P_t) - log(P_{t-1}) \tag{3.1}$$

where P_t is the closing price of the index for day t. The data set of price series exhibited some discontinuities, mainly on holidays [3]. To enable data to be purged from the holiday effect, linear interpolation was implemented. The linear interpolation method is a linear approximation of the missing value calculated as a combination of the previous non-missing value and the next non-missing value:

$$IV_{Linear} = (1 - \lambda)P_{i-1} + \lambda P_{i+1} \tag{3.2}$$

where IV_{Linear} is the interpolated value, λ is the weight coefficient which essentially is the relative position of the missing value divided by the total number of missing values in a row, P_{i-1} is the previous non-missing value and P_{i+1} is the next non-missing value. An example can easily portray the situation. For a single NA value, the interpolated value will be halfway the distance, in our terminology $\lambda = 1/2$. For two NAs in a row, the first value will be interpolated as $1/3$ of the distance between the previous and the next non-missing value computed with $\lambda = 1/3$, while the second value will be interpolated as $2/3$ of the same distance computed with $\lambda = 2/3$. This method will deliver a 5-day sample for each week excluding the weekend where the stock market is closed. This step facilitates the subsequent procedure of rolling regression, where the sample rolls 5 days at a time meaning this way a length of a week.

Table A.1 summarizes the descriptive statistics for the entire sample. All indices exhibit positive mean returns. The highest mean is observed for Health Care sector while Telecommunication Services is the sector with the lowest mean returns. For the unconditional volatility, the highest value is for the Financials and the lowest value for the Consumer Staples sector. All indices are negatively skewed except for Financials, Information Technology, and Telecommunication Services. All values for kurtosis are much greater than three and thus all indices are found to be leptokurtic. Jarque-Bera statistic indicates that none of the indices are normally distributed at 1% level.

The last feature examined is the hypothesis of stationarity. Two test statistics are used for this reason. The first one is the Augmented Dickey-Fuller (ADF) test and the second one is the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. These two tests alternate the hypotheses of stationarity

[3] Discontinuities were observed in the data set on regular public holidays: Christmas, Thanksgiving, Easter, Independence Day, New Year's Eve, Labor Day, Birthday of Martin Luther King, Jr, Memorial Day and President's Day and on irregular market closures (e.g. on days following September 11, 2001).

and existence of a unit root. The ADF is the benchmark one, while the second is often used supplementarily to verify the results. In our data series, both tests conclude to stationarity of the return series, thus our results are indeed robust.

Table A.2 summarizes the descriptive statistics for each day of the week. All indexes exhibit at least one day with negative mean returns except Industrials. Monday mean returns are all positive while negative ones are found in Financials and Materials sectors. Mean returns for Friday are positive for half of the sectors. Highest mean returns are observed on Tuesdays for all indexes except for Consumer Staples, Telecommunication Services and Utilities on Mondays and Consumer Discretionary and Information Technology on Wednesdays. Lowest mean returns are found on Fridays for half of the sectors and the S&P500, on Mondays for Financials and Materials, on Wednesdays for Telecommunication Services and Utilities and on Thursdays for the Energy sector. Highest standard deviation for 7 out of 10 sectors and the S&P500 is observed on Mondays. The lowest standard deviation is found on Fridays for 8 sectors and the S&P500. All days for all indexes exhibit positive or negative skewness and leptokurtosis. The Jarque-Bera statistic rejects the null hypothesis of normally distributed returns for all cases.

3.1.2 NBER's recession indicator

The Business Cycle Dating Committee of the National Bureau of Economic Research, abbreviated as NBER, maintains a record of the business cycle of the U.S. economy. Troughs and peaks succeed one another, developing periods of recessions and expansions. A recession is defined as the time period that intermediates between a peak and a trough. Likewise, an expansion is the period following a trough that ends with a peak. The symptoms of both states are well understood. During a recession, the economic activity drops at substantially low levels and this economic downturn spreads across the whole economy. During an expansion, the economic activity significantly rises, generating a beneficial environment for the development of the various economic sectors. The duration of both phases can fluctuate depending on the existing conditions. Typically, a recession can last from a few months to more than a year, while the duration of an expansion is usually longer, reaching a period of several years.

Of course, periods of recessions or expansions can be interrupted by short periods of reversal route in economic activity. A recession can comprise of a brief period of economic upturn followed by a period of further decline and similarly an expansion can involve a brief period of contraction. Such circumstances are analyzed separately by the Committee who decides whether the alternations are only interruptions of the current full phases. Hence, there is no predetermined rule and the judgment is subject to other various indications.

As both phases are literally based on the economic activity, a definition of what is meant by this terminology is crucial. As it seems, the definition is rather abstract. The Committee's procedure for identifying turning points is different from the two-quarter rule often used by the financial press. It identifies economic activity by a range of factors placing considerable emphasis on monthly indicators as well. The Committee practically studies some broad measures of activity like real GDP traced by both the conventional product side and the equivalent income side, economy-wide employment, and real income. Except for these broad indices, the Committee also considers indicators, like real sales and Federal Reserve's index of Industrial Production, which do not reflect the whole economy. The treatment of both types of measures emerges two problems: that of double-counting some sectors, and the incidence of conflicting results. Still, a well-defined measure could dissolve the difficulties.

We utilized data covering the period between September 11, 1989 and January 6, 2017. Figure 3.2 illustrates business cycles for the U.S. economy in the above-mentioned period. For this time series, the recession starts the first day of the period of the peak and ends on the last day of the period before the trough.

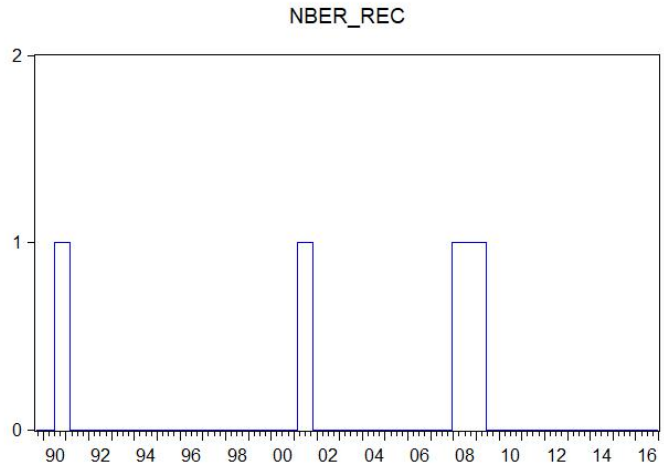

Figure 3.2: The evolution of NBER's recession indicator

3.1.3 News-based Economic Policy Uncertainty index

The news-based Economic Policy Uncertainty index is recorded upon the management of three research directors Baker S., Bloom N. and Davis S. The construction of the index is based on newspaper archives emanated from Access World New's NewsBank service, which serves a database for thousands

of newspaper and other news sources worldwide. This specific index utilizes data that concern US. There are well over 1000 US newspapers covered by NewsBank, from large national newspapers like USA Today to small local newspapers across the country. The data available spans from 1985 to present.

Their elemental strategy is to measure the number of newspapers that contain at least one term of each 3 groups of terms. The first group contains the terms economy or economic, the second uncertain or uncertainty and the third legislation or deficit or regulation or Congress or federal reserve or white house.

A substantial rise in the coverage of newspapers by NewsBank was observed over the years. From a poor level of 18 newspapers in 1985, the number in 2008 surpassed the limit of 1800 and it still increases. In order to account for this growth, a normalization is required. The daily counts of economic policy articles of the total number of newspaper articles are recorded. Baker et al. [2016] presented further details about the index.

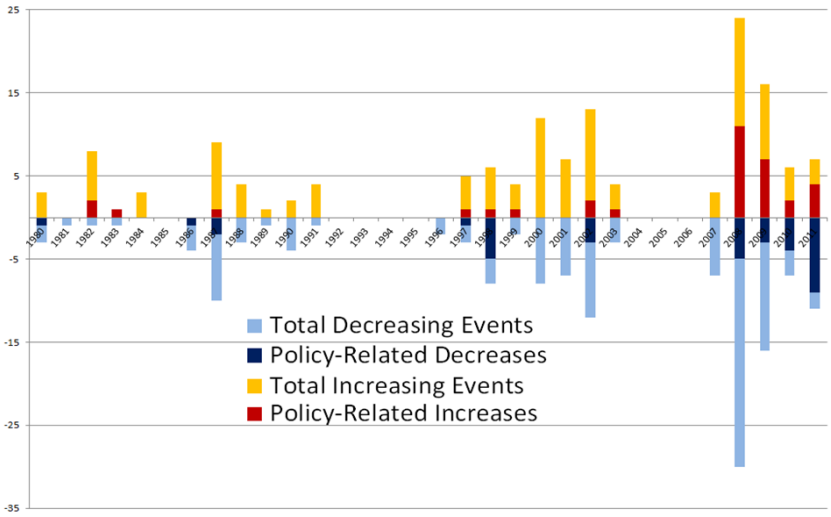

Figure 3.3: The association between large stock movements and policy-related events.

As they pointed in their study, there was detected a drastic increase in the number of large changes in the S&P500 Index, defined as a daily change of more than 2.5%, in recent years compared with the average counterpart since 1980. An interesting finding was that since 2008, the observed large stock movements are progressively associated with policy-related events as was presented in Figure 3.3 [4].

Our sampling period begins in September 11, 1989 and ends on January 6, 2017. Figure 3.4 shows the evolution of the index through time. Descriptive

[4]Source: http://www.policyuncertainty.com/methodology.html

statistics for the index along with the ADF unit root test are summarized in Table A.3. The index is found to be positively skewed, leptokurtic and indeed stationary.

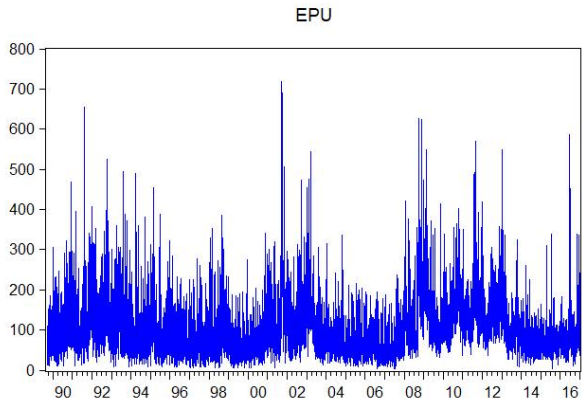

Figure 3.4: The evolution of News' based uncertainty index through time

3.1.4 Trading volume index

Liquidity has a multifaceted notion. Its various aspects – tightness, immediacy, depth, breadth and resiliency – can be partially captured by conventional liquidity measures such as bid-ask spreads, turnover ratios and price impact indices (Sarr and Lybek [2002]). Still, there is no theoretically unique and universally accepted indicator of liquidity, and a construction of such a measure is challenging, if not impossible.

In finance literature, different measures of liquidity have been proposed at individual stock level. However, we are interested in a more general measure that does not focus on the market microstructure. Instead, we are in need of an indicator of long-run systematic changes in market liquidity. In favor of adopting a measure of market liquidity, trading volume was chosen. In trading terms, volume is the number of transactions of a trader or market within a specific time interval. It usually serves as an indication of the prevailing liquidity in a stock or market. Higher volume ordinarily denotes an active market; an increase in the number of transactions typically signals a narrower spread between bid and ask prices.

The NYSE website provides daily total trading volume data as far back as 1888. These volume data include volume in NYSE listed issues executed by NYSE and NYSE Arca. The use of this type of index is motivated by Fishe et al. [1993]. Our sampling period is September 3, 1990 until January 6, 2017. Some detrending would be advisable to prelude in order to remove variability elements and obtain a smoothed measure. For this reason, each daily obser-

vation is divided by the average volume of the week[5]. This index essentially measures whether the daily volume is above or below the weekly average, by whether the observation is above or below unity. This detrended index is then used in our analysis. Descriptive statistics are shown in Table A.3. The data series is negatively skewed, leptokurtic and stationary according to the ADF unit root test.

3.1.5 Bearish sentiment index

The American Association of Individual Investors, AAII, Sentiment Survey is conducted once a week[6]. Each AAII member has been answering the same question about his/her sentiment since 1987. The possible answers are three: bullish, neutral or bearish. Only one vote is accepted per individual in each weekly voting period. The data represents the feeling of the members for the direction of the stock market within the following six months. The results are summarized by analysts and provide a picture of the mood of individual investors.

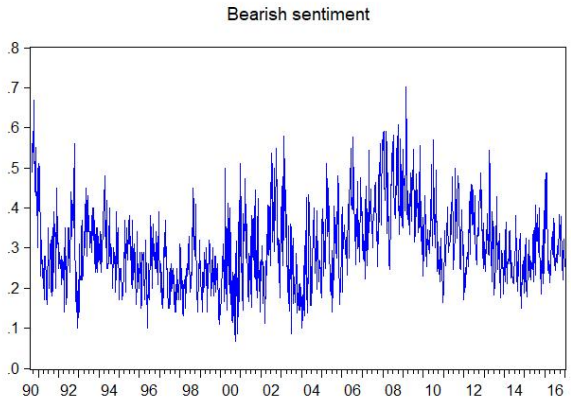

Figure 3.5: Bearish sentiment index over time

We choose to use the percentage of members who are bearish, which offers an indication of pessimism in the stock market, see Figure 3.5. The frequency of this data series is weekly. The descriptive statistics are presented in Table A.3. The index is found to be positively skewed, leptokurtic and stationary based on the ADF unit root test which rejects the null hypothesis of a unit root at 1% significance level.

[5]See Fishe et al. [1993]
[6]Details can be found on the website: http://www.aaii.com/sentimentsurvey

3.2 Econometric Methodology

The first studies discussing day-of-the-week phenomena were employing descriptive statistics. They were initially focusing on the first four moments of the unconditional distribution of returns[7]. Unconditional tests like the ANOVA setting and Kruskal-Wallis were among the most preferred ones to test for daily differences. Another traditional way to detect day-of-the-week effects was through the standard Ordinary Least Squares (OLS) method by regressing stock returns on five daily dummies, each representing a weekday. However, as the implementation of this technique was gaining supporters, some doubted the results. Indeed, OLS methodology has two main drawbacks. Firstly, the error term may be autocorrelated leading to false standard error estimates and misleading inference. In order to account for autocorrelation in the errors, the inclusion of lagged returns in the mean equation up to some specific past time period was later suggested as a cure to properly model the return series. Secondly, OLS assumes constancy of variance of the errors. This assumption is too restrictive when there is evidence in the vast literature backing its time-dependence. Hence, it is completely justified to use models that can capture the evolution of their behavior.

In the next chapter of history related to anomalies, ARCH-type models entered the scene. ARCH is an acronym standing for Autoregressive Conditionally Heteroskedastic models. This type of models except for controlling the observed heteroskedasticity is suitable in the presence of 'volatility clustering' or 'volatility pooling'. 'Volatility clustering' is the tendency for volatility to appear in bunches. Small returns of either sign are followed by small returns and similarly, large returns are accompanied by large returns. In other words, there is a positive correlation between the current level of returns and the levels at immediately preceding time spots.

3.2.1 ARCH-family models

The simplest of this family of models is the ARCH(q) model, introduced by Engle [1982], of the following form:

$$Y_t = X_t'\beta + e_t \tag{3.3}$$

$$e_t|\Omega_{t-1} \sim N(0, h_t) \tag{3.4}$$

$$h_t = \omega + \sum_{i=1}^{q} a_i e_{t-i}^2 \tag{3.5}$$

where X_t may include lagged dependent and exogenous variables and h_t is a function of the previous q squared residuals. Since h_t is a conditional variance,

[7]The first approaches detected daily abnormalities on the first moment. Only later, daily seasonality started to be studied on the following three moments, i.e. those of variance, skewness and kurtosis.

its value must be non-negative. Therefore, some constraints are typically implemented to sustain this condition. Usually, it is required $a_i \geq 0$, for all i's. It should also be noted that this is a sufficient condition but not a necessary one.

Generalized ARCH (GARCH (p,q)) models

As their name would suggest, they are a generalized form of ARCH models, which were introduced independently by Bollerslev [1986] and Taylor [1987]. There is a single but still crucial feature that differentiates them from their ancestors and that is the expression of the volatility equation:

$$h_t = \omega + \sum_{i=1}^{q} a_i e_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{3.6}$$

where the conditional variance is now a function of p previous own values along with the q previous squared residuals. Again, we must confirm the non-negativity of h_t.

Despite the fact that conditional variance is changing over time, the unconditional variance is constant and equal to:

$$Var(e_t) = \frac{\omega}{1 - (\sum_{i=1}^{q} a_i + \sum_{j=1}^{p} \beta_j)} \tag{3.7}$$

Whenever $\sum_{i=1}^{q} a_i + \sum_{j=1}^{p} \beta_j < 1$, unconditional variance exists and the forecasted conditional variance will converge upon its long-term mean as the prediction horizon increases. However, whenever $\sum_{i=1}^{q} a_i + \sum_{j=1}^{p} \beta_j \geq 1$, we say that the variance is non-stationary. Specifically, this convergence will not happen in the case of $\sum_{i=1}^{q} a_i + \sum_{j=1}^{p} \beta_j = 1$ (IGARCH case), while the forecasted value will tend to infinity in case of $\sum_{i=1}^{q} a_i + \sum_{j=1}^{p} \beta_j > 1$.

Exponential GARCH (EGARCH) models

Although GARCH models can account for some stylized facts of financial series like 'volatility clustering' and leptokurtosis, they impose a symmetric response of volatility to positive and negative shocks. Future values of h_t is structured to be determined only by the magnitude of unanticipated excess returns rather than their sign. In practice, volatility tends to rise more facing a negative shock than a positive one of the same size. EGARCH models are part of the asymmetric GARCH models proposed by Nelson [1991]:

$$log(h_t) = \omega + \sum_{j=1}^{q} \beta_j log(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \left(\frac{|e_{t-i}|}{\sqrt{h_{t-i}}} - E\frac{|e_{t-i}|}{\sqrt{h_{t-i}}} \right) + \sum_{k=1}^{r} \gamma_k \frac{e_{t-k}}{\sqrt{h_{t-k}}} \tag{3.8}$$

The above model has two basic advantages: i) Since h_t appears in a logarithmic-form there is no need for artificial imposition of non-negativity constraints on model coefficients. ii) Furthermore, it can capture asymmetry using the rule γ_i should be different from zero. In presence of a leverage effect, where the relationship between returns and volatility is negative, γ_i will be negative. EViews provides a slightly different version of the original Nelson's specification:

$$log(h_t) = \omega + \sum_{j=1}^{q} \beta_j log(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \frac{|e_{t-i}|}{\sqrt{h_{t-i}}} + \sum_{k=1}^{r} \gamma_k \frac{e_{t-k}}{\sqrt{h_{t-k}}} \tag{3.9}$$

and additionally allows distribution of the errors to be either normal, t-distribution or GED opposed to the single Nelson's option of GED.

Generally speaking, GARCH(1,1) and EGARCH(1,1) are sufficient to capture the volatility clustering in the data and rarely larger models are employed by academics in finance. This practice was chosen to be followed in our study as well. To test for daily seasonality, we employ two separate models, those of GARCH(1,1) and EGARCH(1,1) with two choices for the distribution of the errors, the Student's t and the GED distribution as was described above. The mean equation in our case is of the following form:

$$r_t = \beta_1 d_{1t} + \beta_2 d_{2t} + \beta_3 d_{3t} + \beta_4 d_{4t} + \beta_5 d_{5t} + \sum_{i=1}^{k} \alpha_i r_{t-i} + e_t \tag{3.10}$$

where r_t is the continuously compounded return, d_{1t}, d_{2t}, ..., d_{5t} are daily dummy variables for Monday, Tuesday, Wednesday, Thursday and Friday respectively, each taking the value of 1 on the respective day and 0 otherwise, β_1, β_2, ..., β_5 are the corresponding coefficients and e_t is the error term. The number k of the autoregressive terms is determined by the Akaike Information Criterion (AIC)[8].

3.2.2 Rolling regression approach

Estimating coefficients of a model through a rolling window is new to calendar anomalies field. Observed phenomena are questioned to preserve their structure unchanged through time. Generally, rolling estimates can assess the stability of a model over time. The two basic characteristics of rolling regression are the so-called rolling window size and step size.

Window size is the number of consecutive observations used per regression. This basically depends on the sample size. If the time period studied

[8] In the mean equation, constant was omitted in order to avoid the dummy variable trap.

is short, the window size will virtually be quite small while for longer sample sizes, the determination of the window size may be bigger. It is typically argued that longer time horizons tend to yield smoother estimates.

Step size is the number of increments between successive rolling windows.

For example, if the sample size is N, the window size is m and the step size is k, then the procedure incorporates the steps as described below.

The key feature of a rolling estimation is the fixed length of the window. Only the start and end points are moving at each repetition, together, k steps ahead. So, the first subsample contains the first m observations, the second contains the observations from period 1+k through m+k, the third from 1+2k through m+2k etc. At the end, we will end up with a total of $\frac{N-m+k}{k}$ partitions. A regression is estimated upon each subsample and the estimates of each subsample are saved. Usually, a graphical representation of the results can show the objective.

3.2.3 Logit models

When a dummy variable is used as an explanatory variable, usually no problem arises. However, when it is used as the dependent variable, some care should be given and a different methodology should be followed. This kind of models is known as limited dependent variable models, where the qualitative information of the dependent variable can be coded either as finite integers (1, 2, 3, 4 etc) or as binary outcomes (1 for success and 0 for failure). Linear probability models are the simplest form of them. The probability of an event occurring, P_i, is linearly related to some other explanatory variables (factor or continuous) x_{2i}, x_{3i}, ..., x_{ki}:

$$P_i = Pr(Y_i = 1) = \beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + ... + \beta_k x_{ki} + u_i, \qquad i = 1, 2, ..., n \quad (3.11)$$

Logit and probit[9] models belong to this wider class of models but they are additionally designed to overcome two major drawbacks of the linear probability models. First, the latter can produce fitted probability values that are either negative or greater than one. Second, the partial effect of any of the explanatory variables is required to be constant across individuals. Of course, a probability should always lie in the [0,1] interval. Logit and probit models are more sophisticated binary response models, which ensure the validity of this condition through a transformation F:

$$P_i = Pr(Y_i = 1) = F(\beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + ... + \beta_k x_{ki} + u_i) \quad (3.12)$$

[9]Probit is a portmanteau word coming from probability + unit. Logit is a term that is borrowed by analogy from the famous and similar probit model.

In case of logit models, F equals the logistic function, which is the cumulative distribution function (cdf) for a standard logistic random variable:

$$F(z) = \frac{e^z}{1+e^z} = \frac{1}{1+e^{-z}} \tag{3.13}$$

while in the probit case, F is the cdf of a standard normal random variable:

$$F(z) = \int_{-\infty}^{z} \frac{1}{\sqrt{2\pi}} e^{\frac{-v^2}{2}} dv \tag{3.14}$$

Both choices of F are strictly increasing functions, satisfying the following properties: as $z \to -\infty$, $F \to 0$ while as $z \to +\infty$, $F \to 1$.

In fact, logit and probit models can be derived from a subjacent latent variable model. They can be simply seen as the process of finding the β parameters that best fit:

$$Y = \begin{cases} 1 & \text{if } X^T\beta + e > 0, \\ 0 & else. \end{cases} \tag{3.15}$$

where e is an error independent of X and distributed by a standard normal or logistic distribution. The accompanying variable $Y^* = X^T\beta + e$ is called latent variable. It is an auxiliary unobservable variable, since the error term, e, is not observable. The equivalence of two models can be proved easily in a line:

Proof.

$$\begin{aligned} Pr(Y = 1|X) = Pr(Y^* > 0) = Pr(X^T\beta + e > 0) = Pr(e > -X^T\beta) \\ = 1 - F(-X^T\beta) = F(X^T\beta) \end{aligned}$$

□

where the last equality is derived by the symmetry of the normal and logistic distributions about 0.

In most empirical applications, the primary goal is to analyze the effects of each explanatory variable X_j on the response probability $Pr(Y = 1|X)$ and not on Y^*. As it will be illustrated below, the sign of the effect of a change in X_j on $E(Y^*|X) = X^T\beta$ and on $E(Y|X) = Pr(Y = 1|X) = F(X^T\beta)$ is always the same. But the measurement of the latent variable is rarely well-defined (it is often the difference in utilities between two actions). Thus, we are usually not interested on the magnitudes of each β_j as they do not practically have some kind of sense, but on the effects on $Pr(Y = 1|X)$, which are more complex and linked with the nonlinear function F(.).

Here, we will continue with the presentation of the theoretical background of the logit case exclusively because this is the model we are going to use for

demonstration purposes of our results. Since its inception, the logit model was eminent for its computational ease. Nowadays, the evolution of technology does not let this argument to persist, given the computational speeds achieved. The last fact that deserves to be highlighted before proceeding further is that the two models give mostly similar results, so the choice between the two is now up to the researcher.

The logit model is credited to Berkson [1944], who first introduced the term. The model,

$$P_i = Pr(Y_i = 1) = \frac{1}{1 + e^{-(\beta_1 + \beta_2 x_{2i} + \beta_3 x_{3i} + ... + \beta_k x_{ki} + u_i)}}, \qquad i = 1, 2, ..., n \tag{3.16}$$

gives fitted probabilities that have an S-shape bounded from zero and one and allows for different marginal effects across entities. The estimation of the coefficients is assigned to maximum likelihood technique. Unlike linear regression with normally distributed errors, it is impossible to take a closed-form expression of the estimated coefficients that maximize the likelihood function, so an iterative algorithm must be used instead. Neither the interpretation of the estimated coefficients is obvious, as in the linear cases. In order to obtain marginal effects, some calculations must precede. If X_j is a continuous variable, its marginal effect on $Pr(Y = 1|X)$ is given by its partial derivative. Making use of the mathematics, we apply the chain rule and successively get the following type:

$$\frac{\partial P_i}{\partial X_j} = \frac{\partial F(X^T\beta)}{\partial X_j} = F'(X^T\beta) * \frac{\partial X^T\beta}{\partial X_j} = f(X^T\beta) * \beta_j \tag{3.17}$$

where f is the probability distribution function (pdf) of the logistic distribution. Since F(.) is a strictly increasing function, $f(z) = F'(z) > 0$, for all z. Therefore, as it was mentioned earlier, the direction of the effect on Y and Y^* will be the same and only the magnitude will change by the factor $f(X^T\beta)$. If X_j is a dummy variable, its partial effect[10] of changing from the value of 0 to 1, holding all the remaining variables fixed, is simply the difference:

$$\begin{aligned} &F(\beta_1 + \beta_2 x_2 + \ldots + \beta_{j-1} x_{j-1} + \beta_j + \beta_{j+1} x_{j+1} ... + \beta_k x_k) \\ &\qquad - F(\beta_1 + \beta_2 x_2 + \ldots + \beta_{j-1} x_{j-1} + \beta_{j+1} x_{j+1} + \ldots + \beta_k x_k) \end{aligned} \tag{3.18}$$

It is now clear that the marginal effect of a specific explanatory variable is not constant across individuals in both cases. In order to get a single value representing the whole sample, Marginal Effects at the Mean (MEM) or Average Marginal Effects (AME) are used. The formulas for continuous

[10] In case of dummy variables, the notion "partial" instead of "marginal" effects is used. The change of from 0 to 1 should not be accounted for marginal i.e. extremely small increase.

variables are:

$$AME_j = \beta_j \frac{1}{n} \sum_{k=1}^{n} f(\beta X_k), \tag{3.19}$$

$$MEM_j = \beta_j f(\beta \overline{X}) \tag{3.20}$$

and for dummy variables:

$$AME_j = \frac{1}{n} \sum_{k=1}^{n} \left(F(\beta X_k | X_{jk} = 1) - F(\beta X_k | X_{jk} = 0) \right), \tag{3.21}$$

$$MEM_j = F(\beta \overline{X} | \overline{X_j} = 1) - F(\beta \overline{X} | \overline{X}_j = 0) \tag{3.22}$$

In our analysis, we are willing to test for a connection between the existence of daily anomalies and various factors. The results are based on the significance and direction of the effects, i.e. either they are linked to negative or positive returns. To further clarify the situation, the procedure is described in the following lines.

First of all, for each weekday, two-level factor variables are constructed indicating the presence or absence of significant day-of-the-week effects in the rolling time periods. The procedure is now split into three strands. The first factor variable is defined to be unity for cases where significant daily anomalies existed, associated with daily negative mean returns and zero otherwise. Likewise, the second dummy variable is one for significant daily anomalies linked to positive mean returns and zero otherwise. The third and last factor variable is an extended version of the previous two, pointing out significant day-of-the-week effects either bonded to positive or negative mean returns. Let the three versions of probabilities be labeled $psig_{neg}, psig_{pos}$ and $psig$ respectively:

$$psig_{neg} = \begin{cases} 1 & \text{if } p - value < 0.05 \quad \& \quad coef < 0, \\ 0 & else. \end{cases} \tag{3.23}$$

$$psig_{pos} = \begin{cases} 1 & \text{if } p - value < 0.05 \quad \& \quad coef > 0, \\ 0 & else. \end{cases} \tag{3.24}$$

and

$$psig = \begin{cases} 1 & \text{if } p - value < 0.05, \\ 0 & else. \end{cases} \tag{3.25}$$

In a logit estimation setup, we employ these factor variables as dependent variables with explanatory variables being successively the NBER's recession indicator, the uncertainty index, the detrended trading volume and the bearish sentiment index. Average marginal effects are then computed to obtain the objective.

Chapter 4

Empirical results

4.1 Estimation of GARCH-family models on returns

4.1.1 Student's *t*-distribution

Table A.4 presents the Information Criteria for each sector and the S&P500 Index. Four versions are considered, Akaike Information Criterion (AIC), Schwarz's Bayesian Criterion (SIC) and their two modified (healthy) versions, HAIC and HSIC. Information Criteria are used as a guideline for model selection in terms that the suggested model fits best the data. By construction, they provide a measure of information of the trade-off between goodness-of-fit and parsimonious specification of the model. Each is applied to two GARCH-type models, GARCH(1,1) and EGARCH(1,1) models. All Information Criteria indicate EGARCH model to be the winner for the S&P500 Index and all of its 10 sectors.

Table A.5 shows the estimation of the EGARCH(1,1) model under the hypothesis of a Student's *t*-error distribution. The top part of the table consists of the estimated coefficients of the mean equation. The length of the autoregressive part is up to the AIC. The coefficients for Monday are positive and statistically significant for all the indices, most of them at 1% level, lending support to studies suggesting the presence of a 'reverse' Monday effect[1]. All Tuesday coefficients are also positive but statistically significant only for Consumer Staples, Financials, Health Care and Utilities sectors. As for Wednesday, half of the sectors and the S&P500 Index display positive and significant coefficients. Thursday coefficients are positive and significant at 10% only for two sectors: Consumer Discretionary and Health Care. Three negative but not significant coefficients belong to Energy, Financials and the

[1]See for example Mehdian and Perry [2001], Brusa et al. [2003] and Liu and Li [2010].

Utilities sectors. The coefficients for Friday are positive and statistically significant for the Energy sector at 5% level and for Utilities at 1% level. A negative coefficient was detected only for Information Technology sector though not statistically significant.

At the bottom of Table A.5, there are details for the volatility equation followed by some diagnostic checking. The asymmetry term γ is negative and significant at 1% level for all cases, warranting the choice of an asymmetric model to actually capture the existing leverage effect. Beyond that, the constant term is negative and significant in all indices and the coefficients α and β of the absolute value of the lagged residuals and lagged value of the conditional variance are all positive and statistically significant at 1% level. The estimated coefficients for β are below unity for all cases, thus conditional volatility converges upon its long-term average as the prediction horizon increases. We additionally test the stationarity of the conditional variances through three unit root tests. Table A.6 presents the results. All unit root tests confess the stationarity of conditional variances of all sectors at 1% significance level, except the Zivot-Andrews unit root test in the Financials sector which does not reject the null hypothesis of a unit root even at 10% level.

The Ljung-Box statistic shows no evidence of autocorrelation in the standardized squared residuals up to 5 lags for all indexes with exception of four sectors, Energy, Financials, Telecommunication Services and Utilities. The same conclusion of ARCH effects remaining in the structure of only these four sectors is apparent with the help of the Lagrange Multiplier test. Therefore, for these four sectors, the volatility equation is not correctly specified.

Table A.7 shows the results of BDS Independence test on the standardized residuals of the EGARCH specification. The null hypothesis of independent and identically distributed residuals cannot be rejected in half of the sectors, namely Consumer Staples, Financials, Health Care, Industrials and Information Technology. In the remaining sectors, the results are not actually clear taking account both the normal and bootstrapped values. There is probably some nonlinear dependence in the data series that cannot be captured by the EGARCH model.

4.1.2 GED-distribution

Table A.8 informs about the application of the Information Criteria, in this case assuming a GED distribution for the conditional distribution of the innovations. Again, four versions are being used, AIC, SIC and their modified versions HAIC and HSIC. All criteria suggest the use of the EGARCH(1,1) model instead of the simpler GARCH(1,1) model as both appear to show lower values for the EGARCH case.

Table A.9 presents the estimated model for each sector and the S&P500 index, being divided into two subtables. The top one is dedicated to the

mean equation. The length of the autoregressive part is determined individually for each sector so as to minimize the AIC. Lengths from 0 up to 5 are checked. Monday coefficients are all positive and statistically significant except for the Materials sector with a *p-value* nearly exceeding the 10% level of significance. Tuesday coefficients are also positive in all cases but significant for half of the sectors. Similar results are found for Wednesday, too. The coefficients are all positive but significant ones for 6 sectors and the S&P500. Positive and significant coefficients for Thursday belong to Consumer Staples, Health Care and Industrials. Two of the sectors, namely Financials and Utilities exhibit negative expected returns not significant though. Friday results indicate a positive sign for all cases with significant results for Consumer Staples, Utilities and the S&P500 except for Information Technology and Telecommunication Services with negative but not significant coefficients.

The bottom part of Table A.9 contains information connected to the variance equation. Asymmetry term γ is shown negative and statistically significant for all 10 sectors and the S&P500 Index. There is indeed an asymmetry prevailing in the data which is properly captured by the EGARCH specification. Coefficients of the constant term ω, are of a negative sign for all cases even at 1% level. Both α and β coefficients are all positive and significant. Moreover, all estimated values for β are below unity, signaling stationarity of conditional variances in all models. In order to verify this hypothesis of stationarity, three unit root tests are performed and the results are presented in Table A.10. All unit root tests employed vouch for the stationarity of the conditional variance series at 1% level, except for the Zivot-Andrews unit root test in the Financials sector, where the null hypothesis of a unit root is not rejected even at 10% level.

Lastly, some diagnostic checking is able to extract the appropriateness of the model. Ljung-Box statistic rejects the null hypothesis of no autocorrelation in the squared standardized residuals only in 4 sectors. 1% rejection is evident for the Financials and the Utilities sectors and 5% for the Energy and Telecommunication Services. Using the Lagrange Multiplier test, exactly the same results are obtained. Since both types of tests are used for the same purpose of detecting potential ARCH effects remaining in the structure of the data and concerning the fact of the same results obtained, our conclusions are indeed robust. The conditional volatility is misspecified in these 4 cases.

Table A.11 shows the results of BDS Independence test on the standardized residuals of the EGARCH model. The null hypothesis of independent and identically distributed residuals cannot be rejected in half of the sectors, namely Consumer Staples, Financials, Health Care, Industrials and Information Technology. In the remaining sectors, the results are mixed between the normal and bootstrapped procedure, indicating that there is probably some nonlinear dependence in the data series after the EGARCH specification has been fitted.

4.2 Rolling regression method

After running EGARCH(1,1) model with both t and GED distributions for the disturbances in a rolling framework, we obtain the results presented in Tables B.1 and B.2. Window size and step size are fixed to 260 (which is approximately a period of a year) and 5 weekdays respectively. This way, we get totally a set of 1,375 estimations. It is remarkable to mention that the length of the autoregressive part is free to variate through iterations according to the AIC. This property allows more appropriate management of the data and induces a dynamic structure to the rolling technique.

Figures B.1, B.2, B.3 and B.4 offer plots of the rolling *p-values* of the 5 daily dummies and R-squares for the S&P500 Index, where Student's t and GED distributions are used. The figures for all the sectors are similar, therefore not presented here. Their time paths could mirror the evolution of these phenomena when regressions are progressed over time. A clear pattern of unstable abnormalities is actually shown. The variations are large, so the conclusion is honestly simple. Although significant anomalies were detected over the whole sample period, once we evaluate them in a rolling setting, these anomalies are found to be concentrated to specific time periods with lots of ups and downs. On the other hand, given the plots of R-squares, we discover that their value is small oscillating about zero over the entire period, meaning that a small percentage of the total variation of the dependent variable can essentially be explained by each model.

At this point, we introduce a brand new measure[2] of the intensity of the day-of-the-week effects in each sector. This measure is defined for each weekday as the percentage of the statistically significant (at 5% level) coefficients out of the total number of regressions performed:

$$\begin{aligned} i = {} & \% \text{ of statistically significant (at 5\% level) coefficients} \\ & = \frac{\text{number of statistically significant (at 5\% level) coefficients}}{\text{total number of regressions performed}} \end{aligned} \tag{4.1}$$

As this quantity is a single number, cross-sector comparisons can be generated.

EGARCH(1,1) model with t-distributed innovations yields interesting results. Monday reaches the highest intensity among the 5 weekdays for 8 of 10 sectors and the S&P500 Index except for the Consumer Staples and the Telecommunication Services sectors (where it reaches the second largest). The former is exposed to Friday anomalies to a greater extent while the latter to Wednesday anomalies. On the other hand, the weaker anomalies detected are those of Thursday for the S&P500 Index accompanied by the following 4 sectors: Energy, Industrials, Telecommunication Services and Utilities. The

[2]We have encountered the exact measure in Bampinas et al. [2016], as well as a variant in Zhang et al. [2017], which allows comparisons across different rolling windows.

remaining sectors share weakest anomalies on Tuesday, Wednesday and Friday.

EGARCH(1,1) model with GED distributed innovations leads to similar conclusions. The highest intensity of day-of-the-week effects among the 5 weekdays is observed on Monday for all cases except for the Consumer Staples, Information Technology and Telecommunication Services where it is found to be the second largest. The first of these sectors exhibit prominent Friday anomalies whereas the last two Wednesday anomalies. The weakest phenomena are on Thursdays for the S&P500 Index and 4 of its sectors, namely Financials, Industrials, Telecommunication Services and Utilities. The remaining 6 sectors joined by two have lowest percentages on Tuesday, Wednesday and Friday.

Generally, GED yields higher percentage values than the t-distributed counterparts. For the two most documented anomalies that of Monday and Friday, the percentages range from 13.8 to 21.7 and 13.9 to 23.1 for Mondays and 5.7 to 15.3 and 7.1 to 19.1 for Fridays, for t-distribution and GED respectively. Moreover, cross-sector analysis emerges the Monday anomaly the strongest one in both cases. t-distribution offers a 21.7% in the Consumer Discretionary sector, while GED offers a generous 23.1% for the Energy sector.

Tables B.1 and B.2 also inform about the sign of the significant patterns. The vast majority of the significant day-of-the-week effects are produced by positive coefficients with minimal deviations. Extreme cases are those of 43.5% and 40.4% (40.1%, 36.7% using GED) of the total set of significant Monday anomalies which are caused by negative coefficients for Materials and Financials sectors and 70.8% (71.5% in the GED) of Friday for the Information Technology sector. Finally, dominant positive coefficients causing the Friday effect are evident in the Utilities sector with a percentage of 86% (88% using GED).

4.3 Possible explanations

The examination for possible associations between the presence of day-of-the-week effects, derived from the rolling estimations, and various market conditions is presented in this section. The question of whether anomalies are more intense in face of specific conditions is divided into four fronts in order to successively investigate recession, uncertainty, trading activity and bearish sentiment as potential causes. First and foremost, the estimated coefficients and corresponding *p-values* are derived from the rolling regressions of EGARCH models with a GED error distribution. The supplantation of the EGARCH model with Student's t error distributions is done in favor of the stronger anomalies originating from the former specification. Average marginal effects are then computed in a logit framework and displayed in

Tables C.1, C.2 and C.3 below.

Before starting to analyze the behavior of each factor, we must highlight that this methodology is innovative for the literature. None of the existing studies worked with day-of-the-week effects in the dependent variable list. Therefore, our contribution here is catalytic. After presenting our results, we mention previous related studies that tried to offer justification for the anomalies and appear to be in line with our findings, but nevertheless with the application of a different methodology.

4.3.1 Recession

The results for the recession index are initially discussed. It is more likely in recession phases to experience Wednesday and Friday effects for the negative mean returns sample for the S&P500 Index and 7 out of its 10 sectors. Concerning Monday effects, the results are similar, only weaker. These effects are significantly present for only 3 sectors, specifically for Financials, Health Care and Information Technology. The associated marginal effects range from 5% for the second one to around 20% for the first and third one. Only one sector, Energy, shows a rarer event by 9 percentage points. On the other hand, Tuesday effects are less likely to appear in recessions compared to expansions for all sectors except for the Financials sector. Thursday effects are more likely to appear for 4 sectors, namely Energy, Financials, Information Technology and Utilities and less likely to appear for other 4 sectors, namely Consumer Staples, Health Care, Materials and Telecommunication Services.

For positive mean returns, the scenery is opposite. For all weekdays, it is less likely to experience significantly positive mean returns in recessions for most of the sectors. This number of sectors differentiates across weekdays with 5 sectors for Monday, an amazing number of all 10 indices for Tuesday, 4 sectors for Wednesday, 6 sectors for Thursday and lastly 7 sectors for Friday with the exceptions of Consumer Discretionary and Materials which react significantly positively to a recession. It is really remarkable to note that for the broad S&P500 Index it is less likely to have positive phenomena in recessions for all weekdays and the results are all significant at least at 5% level.

As for general significant day-of-the-week effects, either positive or negative, there is a tendency not to meet them in recessions. Consequently, the rule is that the probability of meeting them in expansions is greater according to our findings. Specifically, 7 indices show rarer Monday effects, 9 Tuesday effects, 5 Wednesday effects, 6 Thursday effects and 7 Friday effects. The marginal effects attribute from 4 to 15 percentage points to the above considerations. However, there is not weak evidence for more frequent Friday effects in 4 sectors of Consumer Discretionary, Industrials, Information Technology and Materials with marginal effects reaching from 5% to 24%.

Summing up, for most sectors and days it is more likely to have sig-

nificantly negative day-of-the-week effects in recession periods compared to expansionary ones for 23 out of 55 total cases, less likely to experience positive mean returns for 37/55 cases and less likely to experience general significant phenomena for 33/55 cases. For a detailed description of the logit results associated with the recession's index, see the third column of Table C.4, where fractions of cases with significant linkages to the total number of cases are presented.

There is clear evidence in the paper of Bush and Stephens [2016] for this response of weekday seasonality to a presence of a crisis. In fact, in their research, they divided their sample period into three separate intervals, the pre-crisis period of 1999-2004, the period that contained the crisis 2005-2009 and the post-crisis period of 2010-2012. A substantial increase in the day-of-the-week effects (all of them being positive) was documented in the last period, which actually was believed to be impacted by the crisis, comparing to the former two. Furthermore, Lu and Gao [2016] scrutinized the effect of the global financial crisis on the Chinese stock market. During the financial crisis more negative day-of-the-week effects, especially those related to Tuesday, were observed in contrast to the pre-crisis period of 2003-2008. The tightening of the relationship with the US financial market during the years of the crisis stood as a justification for the changing pattern, ascribing it to a spillover effect.

4.3.2 Uncertainty

We are then occupied with the findings related to the uncertainty indicator. Beginning with the negative mean returns sample, we observe that the probability of a presence of day-of-the-week effects is greater in uncertain times especially on Monday, Wednesday and Friday in 6, 9 and 8 indices respectively. However, in all sectors and all 3 aforementioned days, the marginal effects are extremely small ranging from 0.01% to 0.04%. Thursday presents a weaker number of 3 sectors. On the other hand, Tuesday shows a different pattern, specifically a negative one, for 4 indices. These are the Consumer Staples, Materials and Telecommunication Services together with the S&P500 Index.

Proceeding to the positive day-of-the-week effects, we conclude that Monday effects are more prominent in 5 sectors as the uncertainty increases. The impact of a marginal increase in the uncertainty index, however, will cause a rise in the likelihood of Monday effects by only 0.02 to 0.05 percentage points, a rather small bump. The results for the rest of the days are converse. It is less likely for Tuesday, Wednesday and Friday effects to existing with the growth of uncertainty in 3, 9 and 10 indices respectively. Thursday shows a weak association with this index.

Lastly, the significant effects independent from their sign follow an almost identical pattern with the positive sample above. The relationship between

the seasonality and the uncertainty has a positive sign for Monday but negative for the rest weekdays, except for Thursday which does not depict a strong connection.

Consequently, we conclude that it is indeed more likely to experience stronger negative daily seasonality for 27/55 cases and less likely to meet a positive one for 23/55 cases as the uncertainty rises. These results follow those of Penman [1987] who found a link between the returns and the arrival of news. As he noted, there was a coexistence of negative aggregate earning news on Mondays, which coincides with a high level of uncertainty in our terminology, and negative Monday mean returns. The findings for the general significant phenomena are mixed and depend on the day of the week. For example, Monday exhibits more abnormalities in an uncertain environment while Wednesday and Friday drastically less. Totally, 25/55 cases show a positive association. See the fourth column of Table C.4 for further details.

4.3.3 Trading volume

First, we will discuss the sample with the negative mean returns. Here, there are indeed only a few facts connecting daily abnormalities and trading volume. Only for 3 sectors, the probability of experiencing Monday phenomena is greater as the trading volume increases, tracing out an excess liquidity in the market. These sectors are those of Energy, Health Care and Telecommunication Services. The corresponding marginal impacts are 11.6%, 11% and 5.7% respectively, surely not negligible. Moreover, it is worth noting that the vast majority of the sectors display a positive association but not a statistically significant one at the 5% level.

Then, looking at the positive mean returns sample, we observe that stronger connections exist. It is found that it is more likely to exhibit Wednesday effects for 5 indices, namely Consumer Staples, Financials, Industrials, Utilities and the S&P500 Index. An interesting ascertainment is that the marginal effects for these 5 indices are considerably high. They actually vary from 19% to 24%. On the other side, Monday appears to have a negative correlation. The 3 sectors of Health Care, Industrials and Information Technology justify the fact. Only for one sector that of Information Technology, Thursday effects are more likely to appear with the increase of trading volume.

The last sample is that of all significant effects. Again, the results for this general group is much like those of the positive group above. The differentiation lies on the specific sectors displaying seasonality more likely as the liquidity rises. This time, the 5 sectors for Wednesday effects are Consumer Staples, Financials, Industrials as in the previous case with an addition of the Utilities sector. The corresponding magnitude of the impact is similar; average marginal effects range from 19% to 24%. The probability of Monday effects is smaller for the same 3 sectors as above. A single sector, Energy (-11%), displays less frequently Tuesday effects and another one sector, In-

formation Technology (14.5%), shows more likely Thursday effects in periods of excess liquidity.

To summarize the above results, negative day-of-the-week effects are more likely to appear as liquidity rises in 3 sectors and only for Monday (3/55). This finding weakly supports the study of Fishe et al. [1993] who observed significantly lower Monday returns in a high volume bad news environment, where they defined 'bad news' as the situation of experiencing negative returns on that day. Positive seasonality and general significant patterns behave almost identically with more frequent Wednesday effects and rarer Monday effects for 5 and 3 sectors respectively. For a summary of results concerning the trading volume index, see the fifth column of Table C.4.

4.3.4 Bearish sentiment

The first group we are looking at is that of negative mean returns. The results indicate that it is more likely to have Monday, Wednesday and Friday effects as the bearish sentiment in the market increases. This happens for 8, 3 and 5 indices respectively. The associated marginal effects are quite interesting, ranging from 6,7% to 56.1%. However, it is observed that the probability of experiencing daily anomalies drops in the case of Tuesday for half of the sectors examined as the pessimism rises. Thursday does not show a clear pattern.

We then move to the second group that of the positive mean returns. Here, the connection is much more explicit. It is indeed less likely to have abnormalities as the percentage of bearish investors increases for Monday, Tuesday and Friday with 7, 9 and 9 indices respectively. The drop of the likelihood of experiencing them is from 12.9 to 49.6 percentage points. Only Wednesday is a day with more prominent seasonality for 9 indices with the increase of pessimistic investor sentiment. Again, the behavior of Thursday is vague.

Lastly, we observe the general day-of-the-week effects independent of their sign. Two weekdays, Monday and Wednesday appear to have more frequent anomalies in 3 and 8 indices as the number of bearish investors increases. This association is rather strong, considering the magnitude of the computed marginal effects. Their numbers range from 18.8% to 68.4%. Another two weekdays, Tuesday and Friday show rarer anomalies for 8 and 4 indices respectively. High percentages were detected again, from 13% to 67.5%. Thursday shows a weak connection.

Summarizing the above findings, we would say that it is more likely to meet negative day-of-the-week effects as the bearish sentiment increases for 19/55 cases. As for the positive and general anomalies, the probability of experiencing them drops with the rise of pessimism in the market in 28/55 and 16/55 cases respectively. For a summary of results, see the last column of Table C.4.

Chapter 5

Conclusions

In financial jargon, anomalies reflect situations where the performance of a security or a group of securities contradicts the concept of efficient markets. These anomalies are not expected to appear and they should not persist. Many attempts have been carried out trying to find the foundations laying behind their existence. No conclusive explanations have effectively been formed. Some of them have offered a partial justification of anomalies while others have been rejected. A feeling of a chicken-or-the-egg scenario between them is suspended in the air – which excelled the other is essentially controvertible. The point of unanimity on these lines lies in the fact that historical performance is not a prophet of the future. Every Monday should not be perceived as a catastrophe and every Friday as a salvation. Of course, there will be instances loyal to these anomalies, but this is not always the case.

Our study concentrates on the broad-based S&P500 Index and 10 of its sectors for the period between 1989 and 2017. Our intention is to inspect the presence of day-of-the-week effects both in an aggregate and a sector level, enabling us to distinguish how widespread are the abnormalities across different segments of the market or even a potential focus on specific ones.

The nonlinear models of GARCH and EGARCH are implemented for this purpose. Day-of-the-week effects are present in all sectors, indicating that it seems to be a wide phenomenon spilling over the entirety of the market structure. Using Student's t distribution for the innovations, Monday displays positive and statistically significant returns in all sectors, most of them at 1% level. A reverse Monday effect is therefore found in the whole sample period, which corroborates many recent studies concerning both the US and international markets[1]. Significant results for the other weekdays do exist but are varying in sign. The GED distributed errors yields slightly more, yet similar, day-of-the-week effects.

In all models above for all sectors, the asymmetric EGARCH specification is selected against the symmetric and simpler GARCH one. The coefficients computed warranty the choice of an asymmetric model being able to properly

[1]See for example: Mehdian and Perry [2001], Brusa et al. [2003] and Liu and Li [2010].

capture the existing leverage effect. All asymmetry terms are shown negative and statistically significant, intimating an asymmetric response of volatility to positive and negative shocks. Volatility seems to rise more facing a negative shock than a positive one of the same magnitude.

Rolling regression technique treats seasonality as an evolving phenomenon rather than a stable one. It comes to dispute the above findings of the whole sample. The percentage of significant anomalies is at maximum about 1/5 of the total number of regressions performed. The numbers calculated are even slightly higher for the GED distributed innovations' case. An interesting discovery is the highest percentage of anomalies observed on Mondays. Monday effects are the strongest anomalies compared to the effects of the other weekdays, with Wednesday taking the second place. However, the evidence is weak and fails to support persistent anomalies. The weekday patterns are time-variant and do not show a standard motif.

An effort is then made in the sense of binding the presence of anomalies with specific market conditions in a logit setup. In recessionary phases, it is found that for most sectors and days, it is more likely to experience negative day-of-the-week effects compared to expansionary ones, but less likely to have general significant effects. Bush and Stephens [2016] and Lu and Gao [2016] encountered similar behavior. The second factor employed is the uncertainty index. The analysis concludes that as the uncertainty rises, the probability of negative weekday anomalies increases - a result which is compatible with the study of Penman [1987]. The general significant abnormalities show a mixed structure that depends on the weekday. As a third factor, liquidity is investigated in means of trading volume. In only 3 sectors negative day-of-the-week effects are more likely to appear as liquidity rises, weakly supporting the findings of Fishe et al. [1993]. As for positive and general significant patterns - independent of their direction - more frequent Wednesday effects and rarer Monday effects are detected for 5 and 3 sectors respectively. The bearish sentiment index is the last factor examined. It appears that it is more likely for negative day-of-the-week effects to be present in a bearish environment but less likely for positive and general anomalies. A cross-factor comparison highlights the interactions between recession and uncertainty with the presence of significant anomalies as the most powerful ones.

Although an attempt was made in the way of discovering weekday patterns in sectors of the S&P500 Index, as well as trying to bind them with specific conditions, further research has to be made. The literature has been fertile to date and should continue to be in the future. Other factors suggested to outline weekday anomalies, like characteristics of the market entity or investors' policies, or surprisingly (or not) natural factors such as the weather, can be checked for this case, too. There are undoubtedly no borders for further research. As the famous scientist, Albert Einstein quotes, "If we knew what we were doing, it would not be called research, would it?"

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Appendix A

Whole sample estimations

Table A.1: Descriptive statistics for returns

	Mean	Max	Min	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	ADF (constant, no trend)	KPSS (constant, no trend)
Consumer Discretionary	0.000301	0.123153	-0.101004	0.012456	-0.059556	10.09303	14948.70***	61.64686***	0.066675
Consumer Staples	0.000312	0.088364	-0.092959	0.009272	-0.171572	11.25463	20275.07***	-63.04308***	0.145422
Energy	0.000267	0.169611	-0.168843	0.014511	-0.257589	14.66221	40478.61***	-65.48251***	0.069648
Financials	0.000222	0.172008	-0.186397	0.016960	0.046934	19.52897	81156.46***	-88.11270***	0.166660
Health Care	0.000353	0.117118	-0.091735	0.011479	-0.141282	8.773954	9926.655***	-52.35992***	0.173589
Industrials	0.000278	0.095153	-0.092152	0.011943	-0.286396	9.109953	11186.47***	-83.85888***	0.064870
Information Technology	0.000341	0.160767	-0.100079	0.016387	0.141225	8.501875	9015.334***	-62.08444***	0.117197
Materials	0.000193	0.124728	-0.129327	0.013556	-0.215605	10.57587	17103.57***	-83.27474***	0.019419
Telecom Services	9.58E-05	0.129225	-0.103180	0.012881	0.042294	10.40178	16275.93***	-62.16864***	0.115957
Utilities	0.000134	0.126853	-0.090010	0.010558	-0.048926	14.35978	38334.44***	-85.52890***	0.043816
S&P500	0.000264	0.109572	-0.094695	0.010928	-0.259560	12.36253	26117.79***	-63.66030***	0.118231

Notes: *** denotes significance at 1 % level. Jarque-Bera test checks the rejection or not of the null hypothesis of Ho: normally distributed returns against the alternative of Ha: not normally distributed. ADF is the Augmented Dickey Fuller statistic which tests for the presence of a unit root with Ho: returns have a unit root. KPSS is the Kwiatkowski-Phillips-Schmidt-Shin statistic with null hypothesis Ho: stationary returns.

Table A.2: Descriptive statistics for returns by weekday

		Mean	Max	Min	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	Obs.
Consumer Discretionary	Monday	0.000233	0.096821	-0.092799	0.013221	-0.305346	11.69458	4510.640***	1426
	Tuesday	0.000456	0.123153	-0.058966	0.012355	0.896245	12.30794	5338.636***	1426
	Wednesday	0.000491	0.084667	-0.101004	0.012332	-0.266608	11.62836	4440.382***	1426
	Thursday	0.000350	0.069504	-0.075129	0.012816	-0.207110	7.016095	968.5270***	1426
	Friday	-2.27E-05	0.066273	-0.064577	0.011499	-0.422034	6.409472	733.0204***	1426
Consumer Staples	Monday	0.000714	0.081178	-0.064894	0.009315	-0.023074	12.85168	5762.805***	1426
	Tuesday	0.000663	0.088364	-0.092959	0.009193	0.043057	17.76788	12958.63***	1426
	Wednesday	0.000196	0.075840	-0.062162	0.009155	0.036434	9.345577	2392.808***	1426
	Thursday	0.000102	0.054179	0.066465	0.009444	-0.181165	7.426851	1172.189***	1426
	Friday	-0.000114	0.051675	-0.071785	0.009232	-0.728885	9.154420	2376.784***	1426
Energy	Monday	0.000153	0.169611	-0.115781	0.015402	0.225471	20.55241	18304.74***	1426
	Tuesday	0.000565	0.112769	-0.066235	0.013625	0.523986	8.566181	1906.123***	1426
	Wednesday	0.000341	0.075093	-0.168843	0.015352	-1.078763	16.35633	10876.00***	1426
	Thursday	-8.91E-05	0.105247	-0.121222	0.014967	-0.671746	12.53205	5505.840***	1426
	Friday	0.000367	0.110269	-0.083981	0.013063	0.054261	8.987210	2130.590***	1426
Financials	Monday	-0.000245	0.172008	-0.186397	0.018859	-0.858616	28.04374	37414.42***	1426
	Tuesday	0.000833	0.144820	-0.122536	0.017394	0.938817	17.34282	12432.46***	1426
	Wednesday	0.000434	0.136385	-0.122891	0.016289	0.386861	17.06165	11784.03***	1426
	Thursday	-4.52E-05	0.144152	-0.124886	0.017139	-0.102392	14.95821	8499.000***	1426
	Friday	0.000131	0.105331	-0.080403	0.014866	0.265582	8.927533	2104.407***	1426
Health Care	Monday	0.000573	0.117118	-0.091735	0.012080	-0.301085	14.75015	8219.193***	1426
	Tuesday	0.000811	0.072413	-0.052298	0.011156	0.290620	6.300225	667.2092***	1426
	Wednesday	0.000568	0.064600	-0.069427	0.011468	-0.070560	6.808645	863.0680***	1426
	Thursday	0.000109	0.059454	-0.074159	0.011751	-0.300377	6.921513	935.1691***	1426
	Friday	-0.000297	0.076569	-0.066897	0.010882	-0.286230	7.057603	997.7161***	1426
Industrials	Monday	0.000209	0.073500	-0.088864	0.012594	-0.537213	11.15098	4013.330***	1426
	Tuesday	0.000539	0.095153	-0.055201	0.011770	0.704641	9.667184	2759.157***	1426
	Wednesday	0.000228	0.050991	-0.092152	0.011614	-0.697009	9.448915	2586.514***	1426
	Thursday	0.000381	0.055799	-0.070352	0.012405	-0.457140	8.005521	1538.366***	1426
	Friday	3.18E-05	0.066137	-0.063520	0.011293	-0.390648	6.041015	585.7411***	1426
Information Technology	Monday	0.000600	0.114616	-0.100079	0.016057	-0.254197	9.272082	2351.100***	1426

Table A.2 *(continued)*

		Mean	Max	Min	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	Obs.
	Tuesday	0.000544	0.105528	-0.067480	0.016530	0.444559	7.156952	1073.706***	1426
	Wednesday	0.000964	0.160767	-0.084095	0.017003	0.400338	12.49640	5396.385***	1426
	Thursday	0.000383	0.102554	-0.071287	0.016688	0.261267	6.107979	590.1605***	1426
	Friday	-0.000787	0.084999	-0.078136	0.015589	-0.302994	6.546169	769.0023***	1426
Materials	Monday	-5.23E-05	0.124728	-0.102774	0.014684	-0.071516	12.90462	5825.997***	1426
	Tuesday	0.000343	0.119041	-0.058237	0.013299	0.694092	9.933370	2970.754***	1426
	Wednesday	0.000305	.065544	-0.129327	0.013682	-0.934447	12.92074	6055.380***	1426
	Thursday	0.000102	0.079583	-0.086521	0.013797	-0.495532	7.998954	1543.155***	1426
	Friday	0.000270	0.071662	-0.063768	0.012218	-0.199462	6.022048	552.0945***	1426
Telecom Services	Monday	0.000716	0.129225	-0.103180	0.013712	0.144178	14.80530	8279.745***	1426
	Tuesday	2.19E-05	0.124700	-0.070223	0.013195	0.483727	11.94369	4808.329***	1426
	Wednesday	-0.000217	0.080289	-0.086080	0.013272	-0.251159	8.432588	1768.557***	1426
	Thursday	0.000134	0.083062	-0.074569	0.012521	0.122379	7.065476	985.6036***	1426
	Friday	-0.000175	0.055535	-0.062179	0.011597	-0.473011	6.088103	619.7952***	1426
Utilities	Monday	0.000776	0.126853	-0.067668	0.010800	0.931705	21.16464	19797.19***	1426
	Tuesday	-7.39E-05	0.102197	-0.090010	0.010313	0.067800	16.92565	11523.40***	1426
	Wednesday	-0.000295	0.084839	-0.089981	0.011022	-0.860740	13.30228	6482.389***	1426
	Thursday	-3.24E-05	0.071979	-0.065521	0.010664	-0.127291	9.410684	2445.690***	1426
	Friday	0.000295	0.084177	-0.053620	0.009940	-0.225639	9.274083	2350.985***	1426
S&P500	Monday	0.000340	0.109572	-0.093537	0.011775	-0.496347	18.29427	13947.20***	1426
	Tuesday	0.000523	0.102457	-0.059108	0.010904	0.841029	11.90347	4878.171***	1426
	Wednesday	0.000339	0.055732	-0.094695	0.010609	-0.786369	11.92849	4883.546***	1426
	Thursday	0.000187	0.066923	-0.079224	0.011104	-0.412422	8.902807	2110.688***	1426
	Friday	-7.07E-05	0.061328	-0.063213	0.010194	-0.461669	6.928192	967.4964***	1426

Notes: *** denotes significance at 1 % level. Jarque-Bera test checks the rejection or not of the null hypothesis of Ho: normally distributed returns against the alternative of Ha: not normally distributed. Obs. is an abbreviation for the number of observations in each case.

Table A.3: Descriptive statistics for EPU,detrended trades and bearish sentiment indexes

	Mean	Max	Min	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	ADF (constant, no trend)
EPU	101.1062	719.0700	3.320000	69.01033	1.860050	9.120390	21331.55***	-7.378541***
detrended trades	1.000000	1.674190	0.422462	0.104609	-0.021622	7.612022	6093.719***	-29.55368***
bearish sentiment	0.304364	0.702700	0.066700	0.097335	0.597134	3.245644	85.17088***	-7.073844***

Notes: *** denotes significance at 1 % level. Jarque-Bera test checks the rejection or not of the null hypothesis of Ho: normally distributed returns against the alternative of Ha: not normally distributed. ADF is the Augmented Dickey Fuller statistic which tests for the presence of a unit root with Ho: series has a unit root.

Table A.4: Information Criteria for Student's t-distribution

		Standard ICs		Modified-ICs	
	ICs	AIC	SIC	HAIC	HSIC
Consumer Discretionary	GARCH	-6.338381	-6.326809	-9.137899	-9.126327
	EGARCH	-6.359870	-6.347334	-9.167467	-9.154931
Consumer Staples	GARCH	-6.844858	-6.831355	-9.635606	-9.622102
	EGARCH	-6.856658	-6.847018	-9.653467	-9.643828
Energy	GARCH	-6.014464	-6.000961	-8.825059	-8.811556
	EGARCH	-6.021668	-6.007200	-8.835209	-8.820742
Financials	GARCH	-6.031589	-6.019052	-8.820796	-8.808259
	EGARCH	-6.044868	-6.034264	-8.840260	-8.829656
Health Care	GARCH	-6.391603	-6.379065	-9.178806	-9.166269
	EGARCH	-6.404740	-6.392204	-9.198026	-9.185490
Industrials	GARCH	-6.426306	-6.415700	-9.221666	-9.211060
	EGARCH	-6.445990	-6.434420	-9.249235	-9.237665
Information Technology	GARCH	-5.786115	-5.775509	-8.591099	-8.580493
	EGARCH	-5.799409	-5.788804	-8.610364	-8.599759
Materials	GARCH	-6.162618	-6.152012	-8.962671	-8.952065
	EGARCH	-6.171606	-6.159071	-8.976053	-8.963518
Telecommunication Services	GARCH	-6.240284	-6.231609	-9.035664	-9.026989
	EGARCH	-6.243456	-6.233816	-9.041384	-9.031745
Utilities	GARCH	-6.691822	-6.683147	-8.066299	-8.057624
	EGARCH	-6.695062	-6.685422	-9.494992	-9.485352
S&P500	GARCH	-6.647307	-6.634770	-9.425000	-9.412463
	EGARCH	-6.675631	-6.665992	-9.467255	-9.457615

Notes: AIC stands for the Akaike Information Criterion and SIC for the Schwarz's Bayesian Criterion. HAIC and HSIC are modified versions of the previous two. All information criteria are used for model selection.

Table A.5: Day-of-the-week effects based on EGARCH model with Student's t error distribution

	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecom Services	Utilities	S&P500
Mean equation											
Monday	0.000513**	0.000509***	0.000791***	0.000635**	0.000687***	0.000553***	0.001180***	0.000463*	0.000775***	0.000641***	0.000657***
	(0.0209)	(0.0067)	(0.0037)	(0.0103)	(0.0022)	(0.0097)	(0.0001)	(0.0579)	(0.0018)	(0.0006)	(0.0005)
Tuesday	0.000154	0.000415**	0.000332	0.000414*	0.000598***	0.000286	0.000467	0.000194	0.000157	0.000443**	0.000273
	(0.4867)	(0.0221)	(0.2228)	(0.0898)	(0.0075)	(0.1834)	(0.1109)	(0.4240)	(0.5139)	(0.0226)	(0.1410)
Wednesday	0.000567**	0.000254	0.000258	0.000662***	0.000617***	0.000570***	0.001126***	0.000313	0.000117	4.98E-05	0.000506***
	(0.0101)	(0.150)	(0.3244)	(0.0070)	(0.0051)	(0.0063)	(0.0001)	(0.1957)	(0.6164)	(0.7864)	(0.0061)
Thursday	0.000407*	0.000247	-2.21E-06	-8.81E-05	0.000369*	0.000318	9.14E-05	9.61E-05	0.000243	-0.000118	0.000250
	(0.0565)	(0.1480)	(0.9935)	(0.7076)	(0.0923)	(0.1217)	(0.7486)	(0.6875)	(0.3016)	(0.5197)	0.1675
Friday	0.000271	0.000178	0.000568**	0.000104	5.95E-05	0.000288	-0.000288	0.000325	4.60E-05	0.000649***	0.000231
	(0.2228)	(0.3136)	(0.0343)	(0.6661)	(0.7919)	(0.1677)	(0.3227)	(0.1851)	(0.8492)	(0.0007)	(0.2104)
AR(1)	0.040567***		-0.002808	0.031324***	0.025705**	0.041377***	0.026135**	0.049466***			
	(0.0008)		(0.8096)	(0.0086)	(0.0301)	(0.0005)	(0.0301)	(0.0000)			
AR(2)	-0.013039		-0.026655**		-0.038044***	-0.013126		-0.010629			
	(0.2664)		(0.0236)		(0.0013)	(0.2602)		(0.3615)			
AR(3)	-0.026710**		-0.017718		-0.022940*			-0.000262			
	(0.0239)		(0.1314)		(0.0530)			(0.9821)			
AR(4)			-0.028757**								
			(0.0170)								
AR(5)			-0.023237**								
			(0.0469)								
Variance equation											
ω	-0.229387***	-0.296463***	-0.188274***	-0.206190***	-0.304015***	-0.214978***	-0.185028***	-0.203699***	-0.180157***	-0.255108***	-0.248577***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.134337***	0.149487***	0.129092***	0.152094***	0.151149***	0.124395***	0.131964***	0.134825***	0.124684***	0.159375***	0.127550***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table A.5 *(continued)*

	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecom Services	Utilities	S&P500
β	0.986323***	0.981116***	0.989980***	0.989815***	0.979474***	0.987143***	0.990368***	0.988824***	0.990582***	0.985953***	0.984170***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	-0.094944***	-0.074573***	-0.045607***	-0.080064***	-0.080164***	-0.089680***	-0.069547***	-0.063588***	-0.041505***	-0.038722***	-0.119542***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SE of Regression	0.012454	0.009271	0.014496	0.017000	0.011450	0.011954	0.016390	0.013571	0.012882	0.010559	0.010932
Adj R^2	0.000397	0.000161	0.002454	-0.004581	0.005232	-0.001678	-0.000243	-0.001807	-0.000118	-0.000282	-0.000711
F-test	3.320188***	3.497154***	3.039654	3.326597***	5.244883***	3.890237***	6.935112***	1.507483	2.298837**	5.647251***	4.949752***
	(0.0054)	(0.0037)	(0.0096)	(0.0053)	(0.0001)	(0.0016)	(0.0000)	(0.1838)	(0.0425)	(0.0000)	(0.0002)
LBQ2(5)	2.4646	5.6405	10.933*	20.083***	5.3440	2.8171	6.9137	5.3220	11.229**	31.308***	2.4646
	(0.782)	(0.343)	(0.053)	(0.001)	(0.375)	(0.728)	(0.227)	(0.378)	(0.047)	(0.000)	(0.782)
ARCH(5)	2.446988	5.649307	11.14936**	19.70206***	5.292306	2.818260	6.733842	5.228206	10.72176*	31.44803***	2.446988
	(0.7845)	(0.3419)	(0.0485)	(0.0014)	(0.3813)	(0.7280)	(0.2412)	(0.3887)	(0.0572)	(0.0000)	(0.7845)

Notes: *, ** and *** denote significance at 10%, 5% and 1% respectively. The numbers in parentheses are the corresponding *p-values*. AR(k) is an abbreviation for the autoregressive term of lag k. Adj R^2 is an analogue to R^2 , adjusted for the degrees of freedom. F-test presents the results of testing the hypothesis that all daily coefficients are simultaneously equal to zero. LBQ2(5) is the Ljung-Box test statistic on standardized squared residuals up to 5 lags and ARCH(5) is the the Lagrange Multiplier-test for testing the conditional heteroskedasticity up to 5 lags.

Table A.6: Stationarity of conditional variances using t-distribution

	ADF (SIC)	ADF (t sig)	Phillips-Perron	Zivot-Andrews	
	t-statistic	*t-statistic*	*t-statistic*	*t-statistic*	BP
Consumer Discretionary	-6.983090***	-7.009906***	-7.539550***	-7.447790***	8/12/2011
Consumer Staples	-9.270935***	-8.316557***	-9.337292***	-8.435049***	3/13/1997
Energy	-7.260497***	-7.260497***	-7.252955***	-7.766469***	3/09/2009
Financials	-3.995984***	-3.881802***	-6.169765***	-4.495415	5/15/2009
Health Care	-9.709412***	-8.362236***	-9.790359***	-8.633334***	1/21/1997
Industrials	-6.339719***	-6.508368***	-7.275853***	-7.190299***	8/12/2011
Information Technology	-6.114489***	-5.456569***	-6.185751***	-6.375120***	10/15/1997
Materials	-7.488117***	-7.328228***	-6.897448***	-8.163893***	11/25/2011
Telecom Services	-6.213012***	-6.190652***	-6.316043***	-6.873001***	3/12/2009
Utilities	-7.885462***	-6.948856***	-7.801644***	-7.927851***	3/09/2009
S&P500	-7.367592***	-7.489111***	-8.625319***	-7.854997***	8/12/2011

Notes: ADF and Phillips-Perron unit root tests check whether the conditional variances have a unit root. When only an intercept is included, the critical values are -3.43, -2.86, -2.57 for 1%, 5% and 10% respectively. Zivot-Andrews (1992) tests the hypothesis of a unit root with a single structural break in the data series. For the case of an inclusion of only an intercept, the critical values are -5.34, -4.93 and -4.58 for 1%, 5% and 10% respectively. BP is the specific date of the breakpoint detected. 'SIC' and 't sig' are the two alternative methods of lag length selection in unit root tests.

Table A.7: BDS test statistic on standardized residuals from the EGARCH with t-distribution (*p-values*)

	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecom Services	Utilities	S&P500
BDS statistic Dimension											
2	-0.002038	0.000971	0.001349	-6.06E-07	0.000933	-0.000944	-0.000792	0.001326	0.001458	0.003401	-0.003494
3	-0.003006	0.001873	0.003028	0.001634	0.001340	-0.000466	0.000197	0.003096	0.003187	0.004764	-0.004288
4	-0.004148	0.001314	0.003640	0.002155	0.001057	-0.000574	0.000699	0.004060	0.003808	0.004099	-0.004478
5	-0.003779	0.001171	0.002980	0.002298	0.000648	0.62E-05	0.001282	0.004299	0.004234	0.003235	-0.003770
6	-0.002847	0.001508	0.002864	0.002623	0.000476	0.000636	0.001485	0.004575	0.004615	0.002921	-0.002454
Normal Dimension											
2	0.0189	0.2756	0.1168	0.9995	0.3076	0.2850	0.3661	0.1321	0.1024	0.0002	0.0001
3	0.0291	0.1849	0.0263	0.2535	0.3546	0.7393	0.8872	0.0268	0.0241	0.0008	0.0028
4	0.0113	0.4337	0.0244	0.2041	0.5386	0.7304	0.6715	0.0146	0.0230	0.0154	0.0086
5	0.0266	0.5024	0.0760	0.1919	0.7165	0.9833	0.4542	0.0129	0.0149	0.0656	0.0333
6	0.0826	0.3693	0.0760	0.1209	0.7812	0.7026	0.3671	0.0060	0.0057	0.0836	0.1497
Bootstrap Dimension											
2	0.0000	0.4000	0.0000	1.0000	0.3333	0.3333	0.4667	0.1333	0.0667	0.0000	0.0000
3	0.0000	0.2667	0.0000	0.4000	0.3333	0.9333	0.7333	0.0000	0.0000	0.0000	0.0000
4	0.0000	0.4000	0.0000	0.4000	0.6667	0.8667	0.4667	0.0000	0.0000	0.0000	0.0000
5	0.0000	0.4667	0.0000	0.2667	0.8000	0.7333	0.3333	0.0000	0.0000	0.0667	0.1333
6	0.0667	0.3333	0.0000	0.2667	0.8000	0.6000	0.2667	0.0000	0.0000	0.0667	0.2000

Notes: BDS test statistics are presented in the top part of the table. The second and third sub-tables show the corresponding *p-values* of both normal and bootstrap procedures testing the hypothsesis of Ho: *iid* residuals against the alternative of Ha: not *iid* series.

Table A.8: Information Criteria for GED-distribution

		Standard ICs		Modified-ICs	
	ICs	AIC	SIC	HAIC	HSIC
Consumer Discretionary	GARCH	-6.333394	-6.321823	-9.138994	-9.127423
	EGARCH	-6.353767	-6.343163	-9.167444	-9.156839
Consumer Staples	GARCH	-6.837580	-6.824077	-9.638632	-9.625129
	EGARCH	-6.847672	-6.833204	-9.652705	-9.638237
Energy	GARCH	-6.008215	-5.999540	-8.826088	-8.817413
	EGARCH	-6.016049	-6.006410	-8.836388	-8.826749
Financials	GARCH	-6.028380	-6.014877	-7.129432	-7.115929
	EGARCH	-6.040140	-6.029535	-8.847400	-8.836795
Health Care	GARCH	-6.391045	-6.379473	-9.188722	-9.177151
	EGARCH	-6.402441	-6.389905	-9.204410	-9.191874
Industrials	GARCH	-6.423113	-6.412507	-9.224101	-9.213495
	EGARCH	-6.442350	-6.431745	-9.251197	-9.240592
Information Technology	GARCH	-5.784878	-5.774272	-8.596252	-8.585647
	EGARCH	-5.798246	-5.787641	-8.614457	-8.603853
Materials	GARCH	-6.157356	-6.147715	-8.965631	-8.955990
	EGARCH	-6.166325	-6.155721	-8.977514	-8.966909
Telecommunication Services	GARCH	-6.235578	-6.226903	-9.041118	-9.032442
	EGARCH	-6.238495	-6.228856	-9.045983	-9.036344
Utilities	GARCH	-6.688037	-6.679362	-9.498441	-9.489766
	EGARCH	-6.690312	-6.679707	-9.502717	-9.492113
S&P500	GARCH	-6.647256	-6.635685	-9.433571	-9.421999
	EGARCH	-6.672821	-6.663182	-9.470730	-9.461091

Notes: AIC stands for the Akaike Information Criterion and SIC for the Schwarz's Bayesian Criterion. HAIC and HSIC are modified versions of the previous two. All information criteria are used for model selection.

Table A.9: Day-of-the-week effects based on EGARCH model with GED error distribution

	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecom Services	Utilities	S&P500
Mean equation											
Monday	0.000424*	0.000576***	0.000702***	0.000567**	0.000672***	0.000479**	0.001174***	0.000380	0.000755***	0.000591***	0.000595***
	(0.0531)	(0.0016)	(0.0086)	(0.0183)	(0.0022)	(0.0224)	(0.0001)	(0.1188)	(0.0018)	(0.0015)	(0.0010)
Tuesday	0.000114	0.000477***	0.000234	0.000497**	0.000620***	0.000260	0.000499*	0.000268	0.000103	0.000445**	0.000176
	(0.6010)	(0.0068)	(0.3908)	(0.0393)	(0.0046)	(0.2146)	(0.0821)	(0.2609)	(0.6624)	(0.0210)	(0.3270)
Wednesday	0.000587***	0.000367**	0.000213	0.000725***	0.000524**	0.000562***	0.001164***	0.000296	5.96E-05	7.80E-05	0.000559***
	(0.0078)	(0.0358)	(0.4174)	(0.0028)	(0.0153)	(0.0063)	(0.0000)	(0.2128)	(0.7972)	(0.6636)	(0.0019)
Thursday	0.000338	0.000357**	5.64E-06	-8.42E-06	0.000397*	0.000340*	0.000153	0.000205	0.000174	-0.000139	0.000279
	(0.1111)	(0.0347)	(0.9833)	(0.9710)	(0.0629)	(0.0959)	(0.5867)	(0.3897)	(0.4520)	(0.4463)	(0.1119)
Friday	0.000236	0.000316*	0.000387	9.95E-05	2.89E-05	0.000222	-0.000249	0.000312	-5.61E-06	0.000646***	0.000304*
	(0.2799)	(0.0667)	(0.1415)	(0.6704)	(0.8929)	(0.2748)	(0.3769)	(0.1986)	(0.9810)	(0.0006)	(0.0851)
AR(1)	0.039673***	-0.011463		0.029880**	0.019507*	0.035781***	0.027587**	0.044104***		0.021897*	
	(0.0009)	(0.3243)		(0.0101)	(0.0915)	(0.0021)	(0.0199)	(0.0001)		(0.0568)	
AR(2)		-0.021632*			-0.033967***						
		(0.0617)			(0.0030)						
AR(3)		-0.031344***			-0.026950**						
		(0.0066)			(0.0185)						
AR(4)		-0.017607									
		(0.1234)									
AR(5)		-0.023482**									
		(0.0371)									
Variance equation											
ω	-0.230002***	-0.340402***	-0.191484***	-0.207487***	-0.327292***	-0.222491***	-0.201999***	-0.217484***	-0.185872***	-0.268106***	-0.271002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α	0.128476***	0.162949***	0.123207***	0.148786***	0.156047***	0.119957***	0.136046***	0.134401***	0.121997***	0.158040***	0.128612***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table A.9 *(continued)*

	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecom Services	Utilities	S&P500
β	0.985781***	0.977635***	0.989110***	0.989457***	0.977377***	0.985960***	0.988813***	0.987283***	0.989731***	0.984551***	0.981898***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
γ	-0.095643***	-0.067433***	-0.049942***	-0.076010***	-0.077062***	-0.089548***	-0.070324***	-0.062608***	-0.041409***	-0.039659***	-0.116758***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SE of Regression	0.012458	0.009270	0.014516	0.016997	0.011451	0.011954	0.016391	0.013568	0.012881	0.010567	0.010933
Adj R^2	-0.000248	0.000751	-0.000745	-0.004270	0.005089	-0.001741	-0.000316	-0.001561	-0.000022	-0.001584	-0.000874
LR-test	13.47811**	28.10111***	9.528712*	18.21561***	26.72094***	16.31786***	36.29705***	7.055740	10.79915*	3072.304***	26.07588***
	(0.0193)	(0.0000)	(0.0897)	(0.0027)	(0.0001)	(0.0060)	(0.0000)	(0.2165)	(0.0555)	(0.0000)	(0.0001)
LBQ2(5)	3.4123	4.4317	14.454**	20.955***	4.7297	3.9800	5.8370	7.6190	12.263**	36.080***	2.7140
	(0.637)	(0.489)	(0.013)	(0.001)	(0.450)	(0.552)	(0.322)	(0.179)	(0.031)	(0.0000)	(0.744)
ARCH(5)	3.456138	4.401891	14.60148**	20.46552***	4.693263	3.985826	5.715708	7.384360	11.68277**	36.17932***	2.690886
	(0.6300)	(0.4931)	(0.0122)	(0.0010)	(0.4544)	(0.5515)	(0.3349)	(0.1936)	(0.0394)	(0.0000)	(0.7475)

Notes: *, ** and *** denote significance at 10%, 5% and 1% respectively. The numbers in parentheses are the corresponding *p-values*. AR(k) is an abbreviation for the autoregressive term of lag k. Adj R^2 is an analogue to R^2 , adjusted for the degrees of freedom. LR-test presents the results of testing the hypothesis that all daily coefficients are simultaneously equal to zero. LBQ2(5) is the Ljung-Box test statistic on standardized squared residuals up to 5 lags and ARCH(5) is the the Lagrange Multiplier-test for testing the conditional heteroskedasticity up to 5 lags.

Table A.10: Stationarity of conditional variances using GED-distribution

	ADF (SIC)	ADF (t sig)	Phillips-Perron	Zivot-Andrews	
	t-statistic	*t-statistic*	*t-statistic*	*t-statistic*	BP
Consumer Discretionary	-6.902217***	-6.953624***	-7.486011***	-7.356186***	8/12/2011
Consumer Staples	-9.682593***	-8.408409***	-9.954180***	-8.542451***	3/13/1997
Energy	-7.286071***	-7.286071***	-7.217414***	-7.807179***	3/09/2009
Financials	-3.969401***	-3.860040***	-6.092564***	-4.485704	5/15/2009
Health Care	-9.944588***	-8.338249***	-9.995361***	-8.618642***	1/21/1997
Industrials	-6.311911***	-6.487342***	-7.308082***	-7.176175***	11/25/2011
Information Technology	-6.391812***	-5.502802***	-6.537216***	-6.429949***	10/15/1997
Materials	-7.462856***	-7.306261***	-6.959563***	-8.137774***	11/25/2011
Telecom Services	-6.197432***	-6.159289***	-6.305804***	-6.842780***	3/12/2009
Utilities	-7.891330***	-6.963365***	-7.874214***	-7.942510***	3/09/2009
S&P500	-7.350358***	-7.452457***	-8.830977***	-7.826142***	8/12/2011

Notes: ADF and Phillips-Perron unit root tests check whether the conditional variances have a unit root. When only an intercept is included, the critical values are -3.43, -2.86, -2.57 for 1%, 5% and 10% respectively. Zivot-Andrews (1992) tests the hypothesis of a unit root with a single structural break in the data series. For the case of an inclusion of only an intercept, the critical values are -5.34, -4.93 and -4.58 for 1%, 5% and 10% respectively. BP is the specific date of the breakpoint detected. 'SIC' and "t sig' are the two alternative methods of lag length selection in unit root tests.

Table A.11: BDS test statistic on standardized residuals from the EGARCH with GED-distribution (*p-values*)

	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Information Technology	Materials	Telecom Services	Utilities	S&P500
BDS statistic Dimension											
2	-0.001875	0.000599	0.001509	4.57E-05	0.000790	-0.000855	-0.000948	0.001322	0.001510	0.003535	-0.003549
3	-0.002598	0.001057	0.003502	0.001772	0.001050	-0.000168	-0.000104	0.003109	0.003305	0.004941	-0.004337
4	-0.003585	0.000245	.004291	.002347	0.000660	-0.000167	0.000315	0.004101	0.003985	0.004328	-0.004519
5	-0.003187	4.64E-05	.003694	.002527	0.000227	0.000533	0.000881	0.004350	0.004451	0.003435	-0.003789
6	-0.002270	0.000420	0.003535	0.002867	7.02E-05	0.001180	0.001109	0.004564	0.004857	0.003091	0.002440
Normal Dimension											
2	0.0310	0.5024	0.0797	0.9597	0.3880	0.3335	0.2793	0.1337	0.0907	0.0001	0.0001
3	0.0588	0.4556	0.0101	0.2154	0.4685	0.9045	0.9402	0.0260	0.0193	0.0005	0.0025
4	0.0278	0.8842	0.0078	0.1666	0.7010	0.9200	0.8482	0.0133	0.0173	0.0103	0.0080
5	0.0594	0.9788	0.0272	0.1513	0.8989	0.7573	0.6070	0.0115	0.0104	0.0497	0.0324
6	0.1618	0.8031	0.0276	0.0899	0.9673	0.4766	0.5001	0.0058	0.0036	.0659	0.1517
Bootstrap Dimension											
2	0.0000	0.5333	0.1333	0.7333	0.4667	0.4000	0.4000	0.1333	0.2667	0.0000	0.0000
3	0.0000	0.4667	0.0000	0.3333	0.6667	1.0000	0.9333	0.0000	0.0667	0.0000	0.0000
4	0.0667	0.8667	0.0000	0.2667	0.8000	1.0000	0.8667	0.0000	0.0000	0.0000	0.0000
5	0.0667	0.8667	0.0667	0.2667	0.9333	0.7333	0.5333	0.0000	0.0000	0.0000	0.0000
6	0.2000	0.7333	0.0667	0.2000	0.8000	0.6667	0.5333	0.0000	0.0000	0.2000	0.1333

Notes: BDS test statistics are presented in the top part of the table. The second and third sub-tables show the corresponding *p-values* of both normal and bootstrap procedures testing the hypothsesis of Ho: *iid* residuals against the alternative of Ha: not *iid* series.

Appendix B

Rolling estimation

Table B.1: Percentage of significant coefficients in EGARCH rolling regressions using t-distribution

	Monday			Tuesday			Wednesday			Thursday			Friday			NAs
	% Sign.	% of neg from all sign.	% of pos from all sign.	% Sign.	% of neg from all sign.	% of pos from all sign.	% Sign.	% of neg from all sign.	% of pos from all sign.	% Sign.	% of neg from all sign.	% of pos from all sign.	% Sign.	% of neg from all sign.	% of pos from all sign.	
S&P500	**20.4**	23.9	76.1	14	39.4	60.6	12.6	45.1	54.9	6.9	37.9	62.1	14.6	36.3	63.7	12
Consumer Discretionary	**21.7**	28.9	71.1	14.3	44.2	55.8	9.4	47.3	52.7	11.8	32.7	67.3	14.3	59.2	40.8	12
Consumer Staples	13.8	6.8	93.2	11.7	26.7	73.3	6.5	15.7	84.3	8.3	15.8	84.2	**15.3**	37.9	62.1	15
Energy	**21.2**	34.2	65.8	6.5	42.7	57.3	11.6	56.2	43.8	4.4	78.7	21.3	10.9	36	64	20
Financials	**21.1**	40.7	59.3	7.3	39.6	60.4	11	35.8	64.2	8.5	76.9	23.1	9.1	47.2	52.8	9
Health Care	**21.5**	14.6	85.4	16.2	37.7	62.3	10	20.3	79.7	8.9	27.9	72.1	5.8	25	75	29
Industrials	**18.2**	35.6	64.4	7.4	22.5	77.5	15.7	43.5	56.5	4.1	36.8	63.2	12.5	42.4	57.6	14
Information Technology	**16.4**	15	85	9.3	34.4	65.6	15.7	16.2	83.8	11.3	35.9	64.1	10.5	70.8	29.2	10
Materials	**15.2**	43.5	56.5	12.1	58.7	41.3	7.7	50	50	7	71.9	28.1	5.7	47.4	52.6	20
Telecom Services	17	12	88	13.7	42.6	57.4	**18**	54	46	7.3	43	57	9.5	45	55	26
Utilities	**18.4**	3.6	96.4	12.4	24.6	75.4	12.2	44.6	55.4	8.7	77.3	22.7	10.9	14	86	18

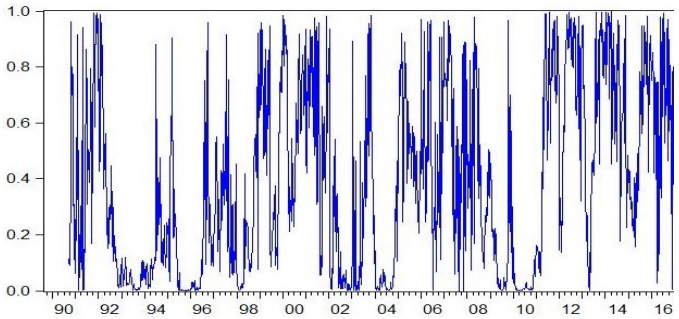
Notes: Rolling regressions are performed with rolling window set to 260 and step size set to 5 weekdays. In each case, the first number denotes the percent of significant coefficients out of the total number of rolling regressions. The second and third numbers following, present the percentage of negative and positive coefficients respectively out of the significant ones across all weekdays. The last column depicts the number of NAs derived out of a total of 1375 rolling regressions performed. (NAs were treated as insignificant results.)

Table B.2: Percentage of significant coefficients in EGARCH rolling regressions using GED (260-5)

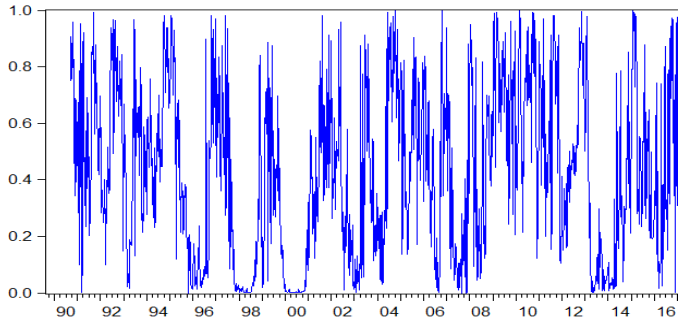
	Monday			Tuesday			Wednesday			Thursday			Friday			NAs
	% Sign.	% of neg from all sign.	% of pos from all sign.	% Sign.	% of neg from all sign.	% of pos from all sign.	% Sign.	% of neg from all sign.	% of pos from all sign.	% Sign.	% of neg from all sign.	% of pos from all sign.	% Sign.	% of neg from all sign.	% of pos from all sign.	
S&P500	**21.7**	23.5	76.5	13.7	41.3	58.7	15.3	39	61	9.2	35.7	64.3	18.3	29.5	70.5	12
Consumer Discre-tionary	**21.7**	27.2	72.8	14.6	50.2	49.8	11.1	34.9	65.1	13.4	35.3	64.7	12.9	58.4	41.6	13
Consumer Staples	13.9	4.7	95.3	13.7	19.1	80.9	7.9	23.9	76.1	10.5	20.8	79.2	**19.1**	38.8	61.2	24
Energy	**23.1**	36.9	63.1	6.8	46.8	53.2	13.2	49.7	50.3	5.4	60.8	39.2	12.2	35.7	64.3	27
Financials	**22.6**	36.7	63.3	9.7	36.8	63.2	13.8	33.7	66.3	9.5	76.3	23.7	11.8	48.8	51.2	9
Health Care	**19.5**	16.4	83.6	17.5	33.7	66.3	11.7	16.1	83.9	10.7	28.6	71.4	7.1	24.5	75.5	41
Industrials	**19.1**	34.4	65.6	8.2	28.3	71.7	16.1	41.4	58.6	5.5	22.7	77.3	15.4	50.5	49.5	8
Information Technology	17.2	21.1	78.9	9.6	41.7	58.3	**19.3**	13.9	86.1	13	30.2	69.8	12	71.5	28.5	8
Materials	**15.1**	40.1	59.9	12.7	56.9	43.1	7.6	45.7	54.3	9	59.7	40.3	7.3	54.5	45.5	28
Telecom Services	17.2	11.4	88.6	13	44.7	55.3	**18.4**	59.7	40.3	8.8	38.8	61.2	10	37.2	62.8	37
Utilities	**17.8**	3.3	96.7	13.4	22.3	77.7	13.6	47.1	52.9	9	78.2	21.8	12.1	12	88	6

Notes: Rolling regressions are performed with rolling window set to 260 and step size set to 5 weekdays. In each case, the first number denotes the percent of significant coefficients out of the total number of rolling regressions. The second and third numbers following, present the percentage of negative and positive coefficients respectively out of the significant ones across all weekdays. The last column depicts the number of NAs derived out of a total of 1375 rolling regressions performed. (NAs were treated as insignificant results.)

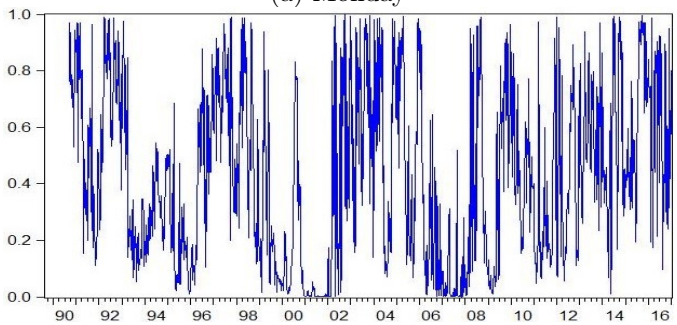
Figures B.1, B.2: Rolling estimates of *p-values* and R-squares of the mean coefficients of EGARCH model with Student's t error distribution - (S&P500 Index)



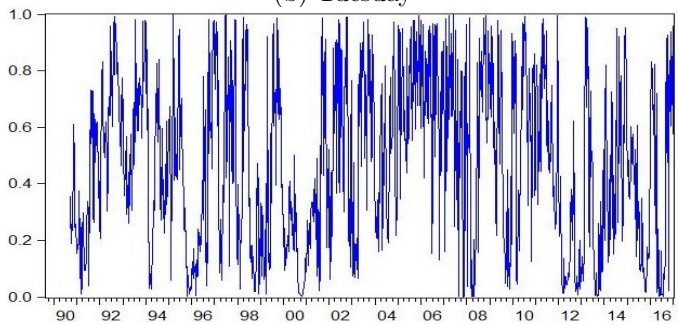
(a) Monday



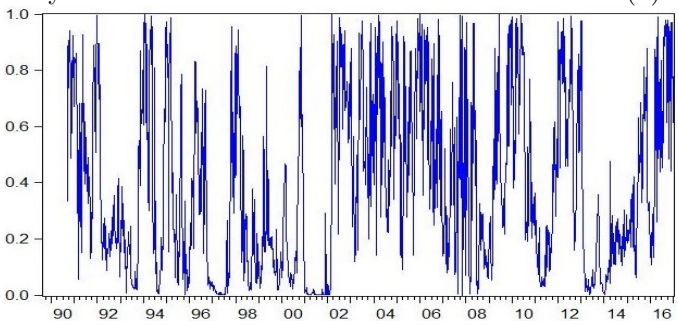
(b) Tuesday



(c) Wednesday



(d) Thursday



(e) Friday

Figure B.1: Rolling *p-values*

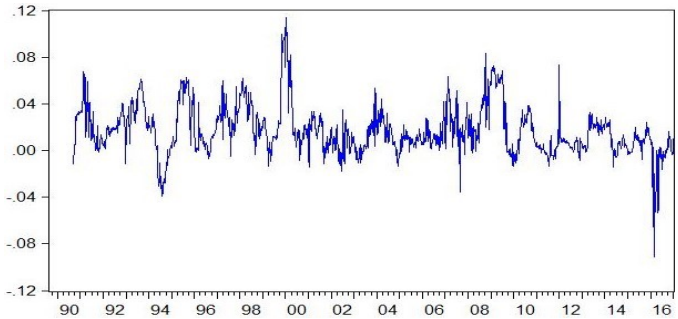
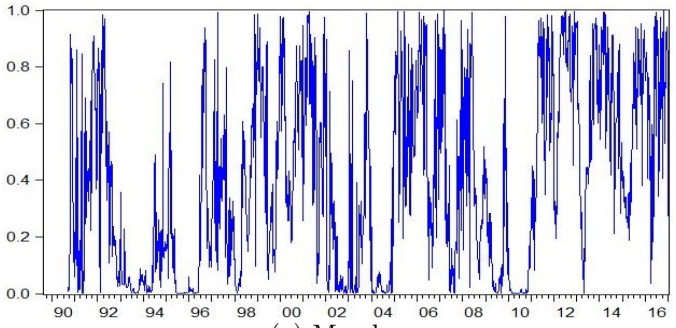
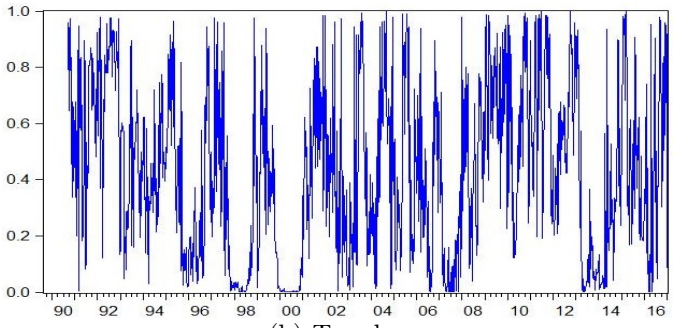


Figure B.2: Rolling R-squares

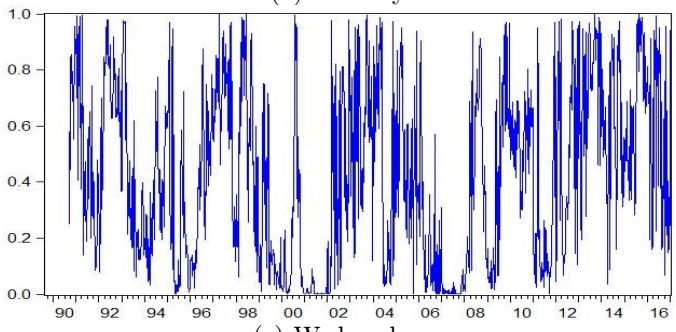
Figures B.3, B.4: Rolling estimates of *p-values* and R-squares of the mean coefficients of EGARCH model with GED error distribution - (S&P500 Index)



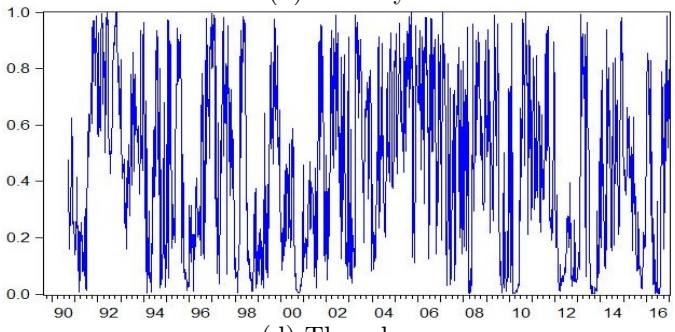
(a) Monday



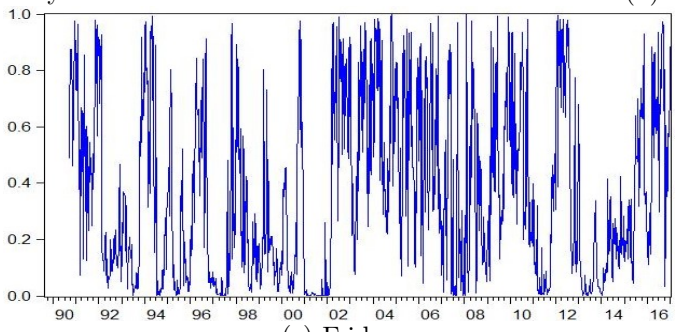
(b) Tuesday



(c) Wednesday



(d) Thursday



(e) Friday

Figure B.3: Rolling *p-values*

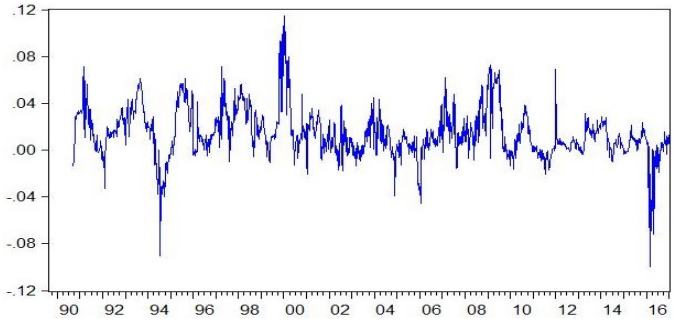


Figure B.4: Rolling R-squares

Appendix C

Logit estimation

Table C.1: Marginal effects of logit (EGARCH-GED) - significantly negative (Group A)

Sector	weekday	recession	uncertainty	trades	bearish sentiment
S&P500	Monday	.0073921	.0001127**	.0602345	.267035***
		0.721	0.019	0.182	0.000
	Tuesday	-.0551035***	-.0003936***	-.0324185	-.2506161***
		0.000	0.004	0.641	0.008
	Wednesday	.2697958***	.0003262***	.0639544	.0116064
		0.000	0.000	0.373	0.875
	Thursday	.0116121	.0000143	.047695	-.0415128
		0.518	0.855	0.292	0.207
	Friday	.2220953***	.0001946***	.0019516	-.0529182
		0.000	0.006	0.963	0.359
Consumer Discretionary	Monday	.0225024	3.40e-06	.004382	.220886***
		0.345	0.960	0.923	0.001
	Tuesday	-.0657086***	-.0000825	-.0923493	.0931828
		0.000	0.407	0.201	0.172
	Wednesday	.1892156***	.0002341***	.0565384	.0468656
		0.000	0.000	0.266	0.435
	Thursday	.0114375	9.13e-06	-.06233069	-.1290251*
		0.580	0.925	0.202	0.095
	Friday	.2461718***	.0002055**	-.0147435	.0508926
		0.000	0.032	0.805	0.477
Consumer Staples	Monday	-0.0041084	-.0000176	.0094093	.0180167
		0.465	0.573	0.248	0.385
	Tuesday	-0.0259355***	-.0002514**	.0264518	-.158203**
		0.000	0.029	0.435	0.014
	Wednesday	.0189809	.0000432	-.0233902	.0309248
		0.242	0.230	0.584	0.411
	Thursday	-.0162685*	.0000208	-.0437632	-.0575768
		0.052	0.740	0.162	0.196
	Friday	.1350216***	.0001946*	.0206539	.2058296***
		0.000	0.058	0.743	0.003

Table C.1 *(continued)*

Sector	weekday	recession	uncertainty	trades	bearish sentiment
Energy	Monday	-0.0914165***	-.0002887**	.1160517**	.0595388
		0.000	0.024	0.040	0.400
	Tuesday	-.0195921*	.000062	.0385693	-.1034435*
		0.084	0.338	0.399	0.098
	Wednesday	.0792473***	.0003007***	.0018202	-.0190549
		0.008	0.000	0.980	0.753
	Thursday	.035622*	.0000614	-.0359153	.0043959
		0.096	0.389	0.436	0.945
	Friday	-.0001757	-.0001109	.0193496	-.1100116
		0.992	0.218	0.653	0.144
Financials	Monday	.195886***	.0003372***	.068328	.5614552***
		0.000	0.000	0.147	0.000
	Tuesday	.0003725	-.0000377	.0006821	.0494747
		0.982	0.790	0.986	0.322
	Wednesday	.3323788***	.0003484***	-.0930684	.2548787***
		0.000	0.000	0.295	0.000
	Thursday	.1511897***	.0000236	.1092446	.2768771***
		0.000	0.822	0.184	0.000
	Friday	.1455603***	.0001877**	.0580623	.0108471
		0.000	0.019	0.314	0.878
Health Care	Monday	.0524377**	.0001224**	.1096365***	.2225883***
		0.025	0.020	0.000	0.000
	Tuesday	-.0495274***	.0001431**	-.0062236	.1517499**
		0.000	0.015	0.911	0.020
	Wednesday	.0509942**	.0001231***	.0450483	.0923863**
		0.016	0.000	0.197	0.015
	Thursday	-.0259773***	.0000961*	-.0089256	.0264292
		0.003	0.072	0.848	0.422
	Friday	.0128174	.0000347	-.0130362	.0670344**
		0.384	0.468	0.430	0.040
Industrials	Monday	-.0167924	.0001631**	.0541184	.3597332***
		0.398	0.017	0.312	0.000
	Tuesday	-.0178867**	-.0000604	-.0480752	.0849669***
		0.034	0.257	0.341	0.005
	Wednesday	.3897581***	.0003833***	.0102474	.263011***
		0.000	0.000	0.914	0.000
	Thursday	-.0057507	.0000416	.0218215	-.0181644
		0.464	0.322	0.498	0.337
	Friday	.2840205***	.0003625***	.0254412	.1875398***
		0.000	0.000	0.617	0.010
Information Technology	Monday	.1996461***	.0002701***	.038928	.3564372***
		0.000	0.000	0.481	0.000
	Tuesday	-.0364951***	-.0000986	-.0539401	-.1415232**
		0.000	0.322	0.245	0.017
	Wednesday	.1941573***	.0001436***	-.0354273	.0472229
		0.000	0.000	0.442	0.279
	Thursday	.0603537**	.000036	.0987773	.0546312
		0.017	0.620	0.123	0.353
	Friday	.2751279***	.0003093***	.052192	.1320961
		0.000	0.002	0.337	0.105

Table C.1 *(continued)*

Sector	weekday	recession	uncertainty	trades	bearish sentiment
Materials	Monday	.0208843	.0001475**	.0374312	.2790476***
		0.381	0.024	0.482	0.000
	Tuesday	-.0480838***	-.0004998***	.0878576	-.2409196***
		0.003	0.005	0.163	0.002
	Wednesday	-.0228283**	.000027	-.0076167	-.2460559***
		0.046	0.661	0.922	0.000
	Thursday	-0.0566549***	.0001611**	-.0086917	-.0715388
		0.000	0.046	0.880	0.215
	Friday	.1891263***	.0002115	.0237312	-.0952155*
		0.000	0.001	0.491	0.068
Telecom Services	Monday	.0181718	.0000437	.0571251**	.1427621***
		0.263	0.252	0.019	0.000
	Tuesday	-.0487183***	-.0002097**	.0178718	-.1075809
		0.000	0.047	0.735	0.199
	Wednesday	.3660334***	.0004204***	-.082179	.0332557
		0.000	0.000	0.455	0.713
	Thursday	-0.034828***	-.000321**	-.0062156	-.0928554*
		0.000	0.015	0.898	0.061
	Friday	.0232095	.0001944***	-.0486852	.153359***
		0.259	0.001	0.160	0.001
Utilities	Monday	.0015308	4.34e-07	-.0307723	-.0674974*
		0.838	0.991	0.142	0.062
	Tuesday	-0.0299775***	-.000026	-.0297815	-.0229327
		0.000	0.583	0.651	0.568
	Wednesday	.0008323	.0002735***	-.0306555	-.0375104
		0.970	0.000	0.691	0.529
	Thursday	.1856301***	.0002773***	-.0505052	.1167539
		0.000	0.002	0.525	0.129
	Friday	.0724345***	.000115***	-.0111368	.0931196***
		0.002	0.002	0.723	0.002

Notes: *, ** and *** denote the 10%, 5% and 1% significance levels. In each case, the marginal effect is presented followed by the associated *p-value*.

Table C.2: Marginal effects of logit (EGARCH-GED) - significantly positive (Group B)

Sector	weekday	recession	uncertainty	trades	bearish sentiment
S&P500	Monday	-.1284429***	.0002075	-.1229501	-.1551277
		0.000	0.149	0.182	0.124
	Tuesday	-0.086566***	-.0003121**	-.0114222	-.2172642***
		0.000	0.037	0.904	0.008
	Wednesday	-.0475367**	-.0008755***	.186324**	.257101***
		0.020	0.000	0.049	0.001
	Thursday	-.0575307***	-6.05e-06	.0133534	.0156113
		0.000	0.944	0.865	0.792
	Friday	-.0947594***	-.0002951*	.0738112	-.0799521
		0.000	0.072	0.353	0.354
Consumer Discre-tionary	Monday	-.1515564***	.000457***	-.0267914	-.3291798***
		0.000	0.001	0.767	0.001
	Tuesday	-0.0776735***	-.0001788	.0784232	-.4801806***
		0.000	0.154	0.331	0.000
	Wednesday	-.0640905***	-.0002472**	.0998748	.2393001***
		0.000	0.047	0.212	0.000
	Thursday	-.0722684***	.0001154	.10698	-.0052491
		0.000	0.237	0.160	0.937
	Friday	0.0565806***	-.0002317**	-.0212991	-.3074445***
		0.000	0.024	0.654	0.000
Consumer Staples	Monday	-.1312425***	.0002388*	-.095029	-.1445059
		0.000	0.074	0.295	0.109
	Tuesday	.1971549***	.0002133**	-.0463706	.0959717
		0.000	0.048	0.610	0.320
	Wednesday	.0448942*	-.0003785**	.1954233**	.470285***
		0.089	0.017	0.014	0.000
	Thursday	-.0842296***	.000124	.0454903	.1052261*
		0.000	0.177	0.536	0.085
	Friday	-.0979345***	-.0005683***	.0345809	-.3901872***
		0.000	0.001	0.603	0.000
Energy	Monday	-.1217958	-.0000133	-.0260008	-.3700877***
		0.000	0.927	0.765	0.000
	Tuesday	-0.0372531***	-6.40e-06	-.1094955	-.2107272***
		0.000	0.924	0.038	0.001
	Wednesday	.0304185	-.0003738	.0630019	-.1707312*
		0.236	0.028	0.402	0.077
	Thursday	-0.0202766***	-.0000123	-.0486802	-.0678564*
		0.002	0.816	0.131	0.065
	Friday	-.0711984	-.0002692	-.0499323	-.4963369***
		0.000	0.083	0.345	0.000
Financials	Monday	.0086844	.0000889	-.0511843	-.3123202***
		0.786	0.519	0.507	0.001
	Tuesday	-.0359479**	.0000514	.0220245	-.2187826**
		0.023	0.517	0.788	0.016
	Wednesday	.0021012	-.0004177***	.2322687**	.3225102***
		0.936	0.005	0.017	0.000
	Thursday	-0.0218633***	.0000851*	.0395041	.0021274
		0.001	0.072	0.451	0.948
	Friday	-.0348787**	-.000613***	.0070518	-.1152125
		0.028	0.001	0.906	0.126

Table C.2 *(continued)*

Sector	weekday	recession	uncertainty	trades	bearish sentiment
Health Care	Monday	-.005157	.0004764***	-.2028081**	-.3577751***
		0.875	0.001	0.039	0.000
	Tuesday	-.1126342***	-.0000261	.0562619	-.4470672***
		0.000	0.835	0.527	0.000
	Wednesday	-.0692068***	-.0010456***	.0948001	.1699167**
		0.000	0.000	0.316	0.035
	Thursday	-.0289283	-.0003564***	.0062292	-.011295
		0.150	0.005	0.932	0.870
	Friday	-0.565806***	-.0002991**	.0249618	-.2730932***
		0.000	0.024	0.525	0.000
Industrials	Monday	-.0431189*	.000208*	-.1749552**	-.0090966
		0.093	0.092	0.043	0.917
	Tuesday	-.0575307***	-.000294**	.0116269	-.2446669***
		0.000	0.031	0.865	0.000
	Wednesday	.0148716	-.0003408**	.1866676**	.4130324***
		0.590	0.028	0.038	0.000
	Thursday	-0.0437203***	-.0000261	.0197592	-.1686723***
		0.000	0.758	0.731	0.000
	Friday	-0.081621***	-.0004847***	.0266675	-.2320829***
		0.000	0.000	0.570	0.001
Information Technology	Monday	-.0152383	-.0000177	-.1640929*	-.2849986***
		0.605	0.897	0.083	0.008
	Tuesday	-.0382878***	-.0004707***	-.0545614	-.2415054***
		0.006	0.002	0.550	0.002
	Wednesday	-.1292519***	-.0002764*	.0941843	.3716944***
		0.000	0.092	0.454	0.000
	Thursday	-.0210996	.0001568	.1448*	-.0442058
		0.368	0.122	0.064	0.563
	Friday	-0.0347713***	-.0008167***	-.0053012	-.3159671***
		0.000	0.000	0.889	0.000
Materials	Monday	-0.0970753***	-.0000152	-.0936792	-.1726283**
		0.000	0.893	0.169	0.029
	Tuesday	-0.0574633***	-.0001807	.0684561	-.4635147***
		0.000	0.133	0.359	0.000
	Wednesday	.01791	-.0002397*	.03298	.1943037***
		0.383	0.056	0.576	0.000
	Thursday	-0.0372531***	-.0000911	-.0799811	.0571002
		0.000	0.136	0.211	0.178
	Friday	.0514159**	-.0002224**	.015317	.1288527**
		0.029	0.027	0.730	0.014
Telecom Services	Monday	-0.1657899***	.000381***	.0157784	-.3557963***
		0.000	0.003	0.847	0.000
	Tuesday	-0.0768651***	-.0000181	.0833447	-.3163232***
		0.000	0.855	0.308	0.000
	Wednesday	-.0665176***	.0000815	.0718252	-.2520743***
		0.000	0.315	0.361	0.002
	Thursday	-.0438639***	-.0000793	.0205558	.0597925
		0.000	0.392	0.770	0.208
	Friday	-0.0662736***	-.0007315***	.0265315	-.2988576***
		0.000	0.000	0.586	0.000

Table C.2 *(continued)*

Sector	weekday	recession	uncertainty	trades	bearish sentiment
Utilities	Monday	.0723616*	.0000984	-.0749837	.1319633
		0.054	0.523	0.408	0.214
	Tuesday	-.0116529	-.0001871	-.0311866	-.0178758
		0.657	0.190	0.765	0.850
	Wednesday	-.0160706	-.0002343*	.2361459***	.3845994***
		0.447	0.068	0.003	0.000
	Thursday	-0.0186598***	3.74e-06	-.0018613	-.0175008
		0.004	0.923	0.954	0.454
	Friday	-0.1155467***	-.0008525***	.0899271	-.3871268***
		0.000	0.000	0.141	0.000

Notes: *, ** and *** denote the 10%, 5% and 1% significance levels. In each case, the marginal effect is presented followed by the associated *p-value*.

Table C.3: Marginal effects of logit (EGARCH-GED) - all significant (Group C)

Sector	weekday	recession	uncertainty	trades	bearish sentiment
S&P500	Monday	-.1284429***	.0002075	-.1229501	.1526363
		0.000	0.149	0.182	0.168
	Tuesday	-0.1416703***	-.0003121**	-.0114222	-.461215***
		0.000	0.037	0.904	0.000
	Wednesday	-.0475367**	-.0008755***	.186324**	.275679***
		0.020	0.000	0.049	0.005
	Thursday	-.0575307***	-6.05e-06	.0133534	-.0245061
		0.000	0.944	0.865	0.718
	Friday	-.0947594***	-.0002951*	.0738112	-.1323991
		0.000	0.072	0.353	0.185
Consumer Discre-tionary	Monday	-.1515564***	.000457***	-.0267914	-.0696474
		0.000	0.001	0.767	0.546
	Tuesday	-0.1434202***	-.0001788	.0784232	-.324438***
		0.000	0.154	0.331	0.002
	Wednesday	-.0640905***	-.0002472**	.0998748	.289935***
		0.000	0.047	0.212	0.001
	Thursday	-.0722684***	.0001154	.10698	-.1278899
		0.000	0.237	0.160	0.177
	Friday	0.1574949***	-.0002317**	-.0212991	-.2209493**
		0.000	0.024	0.654	0.022
Consumer Staples	Monday	-.1312425***	.0002388*	-.095029	-.1238418
		0.000	0.074	0.295	0.178
	Tuesday	.1971549***	.0002133**	-.0463706	-.036023
		0.000	0.048	0.610	0.744
	Wednesday	.0448942*	-.0003785**	.1954233**	.5140875***
		0.089	0.017	0.014	0.000
	Thursday	-.0842296***	.000124	.0454903	.0546279
		0.000	0.177	0.536	0.452
	Friday	-.0979345***	-.0005683***	.0345809	-.1394306
		0.000	0.001	0.603	0.211
Energy	Monday	-.1217958***	-.0000133	-.0260008	-.2948913***
		0.000	0.927	0.765	0.008
	Tuesday	-0.0569206***	-6.40e-06	-.1094955**	-.3096272***
		0.000	0.924	0.038	0.000
	Wednesday	.0304185	-.0003738**	.0630019	-.1844383*
		0.236	0.028	0.402	0.081
	Thursday	0.0149064	-.0000123	-.0486802	-.0593104
		0.502	0.816	0.131	0.427
	Friday	-.0711984***	-.0002692*	-.0499323	-.5907881***
		0.000	0.083	0.345	0.000
Financials	Monday	.0086844	.0000889	-.0511843	.3575326***
		0.786	0.519	0.507	0.002
	Tuesday	-.0359479**	.0000514	.0220245	-.15333
		0.023	0.517	0.788	0.117
	Wednesday	.0021012	-.0004177***	.2322687**	.5857878***
		0.936	0.005	0.017	0.000
	Thursday	0.1278525***	.0000851*	.0395041	.2852996***
		0.000	0.072	0.451	0.000
	Friday	-.0348787**	-.000613***	.0070518	-.1006216
		0.028	0.001	0.906	0.310

Table C.3 *(continued)*

Sector	weekday	recession	uncertainty	trades	bearish sentiment
Health Care	Monday	-.005157	.0004764***	-.2028081**	-.0731156
		0.875	0.001	0.039	0.509
	Tuesday	-.1126342***	-.0000261	.0562619	-.2508863**
		0.000	0.835	0.527	0.022
	Wednesday	-.0692068***	-.0010456***	.0948001	.2676423***
		0.000	0.000	0.316	0.002
	Thursday	-.0289283	-.0003564***	.0062292	.0157686
		0.150	0.005	0.932	0.834
	Friday	-0.0439587***	-.0002991**	.0249618	-.1745504**
		0.009	0.024	0.525	0.018
Industrials	Monday	-.0431189*	.000208*	-.1749552**	.3880244***
		0.093	0.092	0.043	0.000
	Tuesday	-.0575307***	-.000294**	.0116269	-.1299593*
		0.000	0.031	0.865	0.058
	Wednesday	.0148716	-.0003408**	.1866676**	.6839332***
		0.590	0.028	0.038	0.000
	Thursday	-0.0495122***	-.0000261	.0197592	-.1848042***
		0.000	0.758	0.731	0.000
	Friday	0.2000413***	-.0004847***	.0266675	-.0142607
		0.000	0.000	0.570	0.887
Information Technology	Monday	-.0152383	-.0000177	-.1640929*	.1800762*
		0.605	0.897	0.083	0.098
	Tuesday	-.0382878***	-.0004707***	-.0545614	-.3803557***
		0.006	0.002	0.550	0.000
	Wednesday	-.1292519***	-.0002764*	.0941843	.4204889***
		0.000	0.092	0.454	0.000
	Thursday	-.0210996	.0001568	.1448*	.0130995
		0.368	0.122	0.064	0.889
	Friday	0.2380057***	-.0008167***	-.0053012	-.1123799
		0.000	0.000	0.889	0.279
Materials	Monday	-0.076709	-.0000152	-.0936792	.147457
		0.003	0.893	0.169	0.117
	Tuesday	-0.1056907***	-.0001807	.0684561	-.6750227***
		0.000	0.133	0.359	0.000
	Wednesday	.01791	-.0002397*	.03298	.0170287
		0.383	0.056	0.576	0.830
	Thursday	-0.0970753***	-.0000911	-.0799811	-.0093551
		0.000	0.136	0.211	0.894
	Friday	.0514159**	-.0002224**	.015317	.0530219
		0.029	0.027	0.730	0.475
Telecom Services	Monday	-0.1478606***	.000381***	.0157784	-.1671444
		0.000	0.003	0.847	0.112
	Tuesday	-0.1256352***	-.0000181	.0833447	-.4153619***
		0.000	0.855	0.308	0.000
	Wednesday	-.0665176***	.0000815	.0718252	-.2016343*
		0.000	0.315	0.361	0.077
	Thursday	-.0438639***	-.0000793	.0205558	-.0246103
		0.000	0.392	0.770	0.710
	Friday	-0.0434532**	-.0007315***	.0265315	-.0934954
		0.049	0.000	0.586	0.269

Table C.3 *(continued)*

Sector	weekday	recession	uncertainty	trades	bearish sentiment
Utilities	Monday	.0723616*	.0000984	-.0749837	.0837185
		0.054	0.523	0.408	0.443
	Tuesday	-.0116529	-.0001871	-.0311866	-.0405389
		0.657	0.190	0.765	0.687
	Wednesday	-.0160706	-.0002343*	.2361459***	.3782327***
		0.447	0.068	0.003	0.000
	Thursday	0.1653164***	3.74e-06	-.0018613	.1019107
		0.000	0.923	0.954	0.210
	Friday	-0.0436798*	-.0008525***	.0899271	-.2553475***
		0.083	0.000	0.141	0.004

Notes: *, ** and *** denote the 10%, 5% and 1% significance levels. In each case, the marginal effect is presented followed by the associated *p-value*.

Table C.4: Summary results based on logit estimations (number of significant coefficients)

		recession		uncertainty		trading volume		bearish sentiment	
Group A	*Neg & Pos*	16/55	**23/55**	6/55	**27/55**	0/55	**3/55**	10/55	**19/55**
	Total sign.	39/55		33/55		3/55		29/55	
Group B	*Neg & Pos*	**37/55**	5/55	**23/55**	7/55	3/55	**6/55**	**28/55**	11/55
	Total sign.	42/55		30/55		9/55		39/55	
Group C	*Neg & Pos*	**33/55**	9/55	**25/55**	7/55	4/55	**6/55**	**16/55**	12/55
	Total sign.	42/55		32/55		10/55		28/55	

Notes: Groups A, B and C consist of negative, positive and general significant day-of-the-week effects respectively. For each group, each ratio depicts the total number of cases with significant (negative and positive) coefficients out of a total of 55 marginal effects (55=5 weekdays * 11 indices) from the logit estimations above.