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Financial markets and anomalies – the weekend effect

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ABSTRACT

This paper's main objective is for one to test whether the weekend effect in the context of financial markets, i.e. higher stock returns on Fridays and lower stock returns on Mondays, is present among nine selected European stock indices under study and for another to examine whether investor sentiment is able to explain this market anomaly. The presented statistical analyses reveal that the traditional interpretation of the weekend effect, which implies the direct comparison between Monday and Friday returns, is of existence in the data under study as I find that Monday returns are significantly lower compared to Friday returns, ceteris paribus. Even though this finding is statistically significant at the 5% level, the magnitude of the effect is rather low as the fixed effects regression outputs show that the estimated difference in returns between Monday and Friday lies below 0.1%. Furthermore, I provide statistical evidence that investor sentiment as indirectly measured by average daily returns of German government bonds with a duration of 10 years to a limited extent is capable of explaining the weekend effect from a behavioural point of view. Based on a popular three-step approach for mediation testing, I find that average daily returns of German government bonds with a duration of 10 years serve as a valid mediator variable for the weekend effect. Additional effect path analyses based on structural equation modelling (SEM) reveal that the degree to which this indirect proxy of investor sentiment drives the weekend effect lies below 5% and thus can be considered as rather insignificant from an economic perspective.

This paper provides interesting insights into weekly patterns in stock returns among indices that have experienced little to no interest by researchers in the context of examining the weekend effect to date. Similar to the well-document weekend effect among US stocks, the detected traditional weekend effect among selected European stock indices is small in size. Therefore, trading strategies that aim to exploit this market anomaly are likely to turn out unprofitable since trading costs and noise trader risk would offset a possible, small gain. Intraday analyses of stock returns, as well as the application of direct measures of investor sentiment within appropriate statistical models, constitute promising areas for future research in regards to the weekend effect that would provide further meaningful insights into this puzzling anomaly.

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1. Introduction

In 2013, Eugene F. Fama, Robert J. Shiller and Lars Peter Hansen collectively were awarded the Nobel Memorial Prize in Economic Sciences for their "empirical analysis of asset prices".[1] Already 43 years earlier to that honour, Fama (1970) first introduced his groundbreaking findings on the efficiency of capital markets and formulated the eminent efficient-market hypothesis that shaped economic education since then. The weak form of this mathematical-statistical economic theory claims that prices of traded assets already reflect all past publicly available information. The semi-strong form of market efficiency, in turn, describes the assertion that (asset) prices incorporate all publicly available information whereas the strong form of market efficiency predicates that prices fully reflect all available private information.

In contrast to markets that are considered as less efficient like the real estate/ housing or the job market, previously outlined market efficiency assumptions might especially hold for financial markets like the stock market since buyers and sellers have all available and relevant company information on-hand and immediately react to new incoming information. Furthermore, stronger forms of market efficiency might particularly be valid for the current era of algorithmic trading, which is characterised by supercomputers that conduct high-frequency trading (HFT) and therefore almost instantly react to news or changing factors regarding a company's stock price. Therefore, in the presence of the weak or semi-strong form of market efficiency, investors should not gain an information advantage (and consequently an excess return) by basing their trading decisions on past price or volume movements or their valuation outcomes of performed technical or fundamental analyses. However, this is only what the underlying traditional economic theory looks like, in practice, we find that the stock market as a paradigm of an efficient market does not seem to be as efficient as conventional economic theory predicts. Warren E. Buffett, an American business magnate and investment legend, might serve as the living proof for inefficiencies in the stock market and that stocks precisely not follow a random walk as he was (and still is) beating the stock market for over half a century now, making him one of the wealthiest individuals of our time.

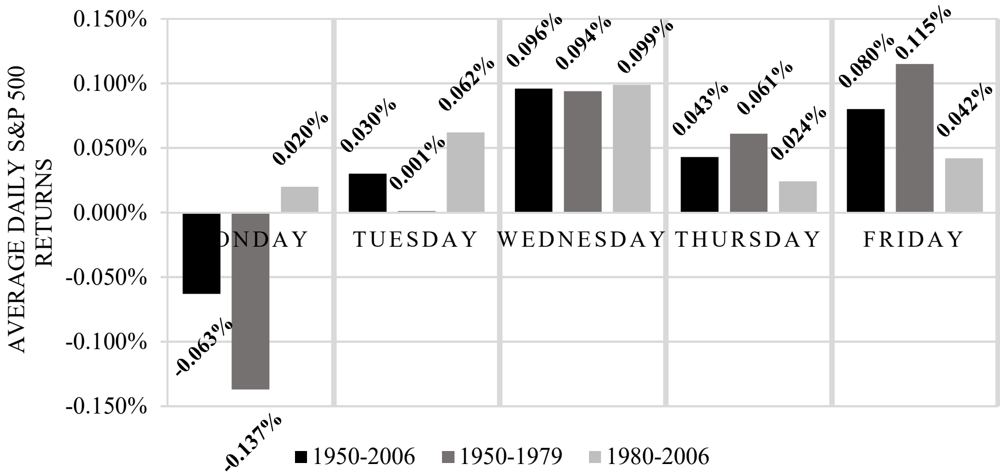
[1] The Royal Swedish Academy of Sciences, 'The Prize in Economic Sciences 2013', *Press release 14-10-2013* https://www.nobelprize.org/nobel_prizes/economic-sciences/laureates/2013/press.pdf [accessed 07-06-2018]

In addition to this, empirical economic research on asset prices reveals that asset/ stock prices often deviate from its fundamental value as well as in many cases follow a specific pattern in the absence of any apparent fundamental or economic reason. These patterns in stock prices that frequently persist over many years are referred to as market anomalies and cannot be fully explained by rational explanations yet (Miller & Jordan, 2008). According to related literature, market anomalies typically feature three characteristics: first, market anomalies are rather small in size or magnitude relative to the overall stock market size. Second, some market anomalies appear to be fleeting or transitory and vanish after their discovery while others tend to exhibit strong persistence over many years. Third, trading strategies that aim to exploit market anomalies are rather unattractive from an investor perspective since high transaction costs on the one hand, and only small deviations from the fundamental value on the other hand, render their exploitation unprofitable (Miller & Jordan, 2008).

Specific types of market anomalies can be categorised as time series or calendar anomalies including (but not limited to) the Monday effect, day-of-the-week effect, weekend effect, January effect, turn-of-the-month effect, holiday effect, time-of-day effect, momentum, overreaction. The variant formulations of daily seasonality in stock returns have emerged from an extensive body of research reaching back to the late 1920s with the Monday effect being the strongest of the calendar anomalies (i.a. Rubinstein, 2001). The Monday effect describes the tendency of stock returns to be lower on Mondays compared to those for Tuesday through Friday (French, 1980; Kamara, 1997). Furthermore, most studies that examined the Monday effect found that Monday not only features the lowest return during a week but also exhibits the only negative return during a week. To highlight the relevance of the Monday effect and latter mentioned observation, Rubinstein (2001) stated that "the 1928–87 period encompassed 12 nonoverlapping five-year periods, and in every one, Monday was not only negative but it was also the worst day of the week. […] Furthermore, of the 55 overlapping five-year periods in the 1928–87 period, Monday was always negative and, in all but one, was the worst day of the week."

The weekend effect, in turn, describes the direct relationship between Monday and Friday returns (Cross, 1973) whereas the day-of-the-week effect (Ke et al., 2007) or weekday effect describes that weekdays differ in their expected returns during a week (Doyle & Chen, 2009). In regards to the above mentioned three effects and assessments of day seasonality in stock returns, the day-of-the-week effect can be considered as a more general observation of daily-based patterns in stock returns whereas both the Monday effect as well as the weekend effect reflect findings derived from a more narrow and focused perspective. However, there is no consensus in related financial/ academic literature on the underlying causes and reasons for these observed day-based calendar effects as well as whether and why these market anomalies are persistent in so many markets and for so many years.

Figure 1. Average daily S&P 500 returns by weekday (dividends included)
(in reference to Miller & Jordan, 2009)



This paper contributes to the existing literature on the one hand by examining the existence and magnitude of a weekend effect across nine selected European total return stock indices that have experienced little to no interest by researchers examining calendar anomalies up to now. A positive finding of significantly lower returns on Mondays compared to Fridays could provide investors an indication on how to steer their investment decisions in order to capitalize on this market anomaly. Since the magnitude of a potential weekend effect is presumed to be rather small, a significant return difference between Monday and Friday might be of special interest for institutional investors, who transfer large amounts of money and have vanishing small transaction costs, thus might be able to trade on the weekend effect or at least should consider this anomaly in their investment decisions.
The weekend effect analysis presented in chapter 3.3.1 examines the presence of a weekend effect in the data under study based on different perspectives on the relationship between Monday returns and Friday returns by comparing returns on these days to different weekdays or inter-weekly periods as reference categories in the statistical models. I am able to provide statistical evidence that the traditional interpretation of the weekend, which involves the direct comparison between Monday and Friday returns, is present in the data under study by featuring significantly

higher returns on Friday compared to Monday, however, the detected difference in returns is only small in size.

This paper contributes to the existing literature on the other hand by testing if behavioural explanations are able to explain a potential weekend effect in the data under study at least to a small extent. The behavioural explanations for the weekend effect embrace the assumption that mood states of investors or more generally investor sentiment fluctuate during a week. For one thing, a typical investor's mood tends to be better on Fridays compared to the other weekdays since the weekend lays ahead of him, ultimately leading to higher stock returns on average. For another thing, a typical investor might experience a rather lousy mood on Mondays since leisure time is now over and the new workweek just started, which finally leads to a decrease in stock prices on that weekday. The analysis of behavioural explanations for the weekend effect is presented in chapter 3.3.2 and examines whether indirect proxies of investor sentiment are capable of explaining significantly higher returns on Friday compared to Monday. I provide statistical evidence that the traditional weekend effect to a small extent is driven or affected by investor sentiment as indirectly measured by average daily returns of German government bonds with a duration of 10 years. Increases in prices of German government bonds are associated with decreases in investor sentiment since they reflect an increase in the demand of assets that are considered as safe and as of high quality, which in turn indicates tension in the market or even fear among investors. Ultimately, this gives an indication that investors' trading decisions are affected by their mood which in turn tends to be determined to some extent by the day of a week. Thus, investors do not behave as fully rational as conventional economic theory assumes.

2. Related literature and previous findings

In regards to the structure of this chapter, I first start with presenting an overview of the existing body of knowledge and various findings regarding the weekend effect including possible rational explanations for this pricing anomaly, followed by a brief introduction of the existing psychological literature regarding mood fluctuations during a week. Following this, I build the bridge between (daily) variations in investor mood and financial markets by giving insights into related previous findings and finally, I present outcomes of academic papers that precisely examined the relation between investor mood/ sentiment and the weekend effect.

2.1. The weekend effect – ancient discoveries

Interestingly, Fred C. Kelly, the very first person who discovered that Monday stock returns are inferior to returns on any other weekday, attributed his finding to behavioural explanations. Already in the late 1920s, the American newspaperman and author dealt with this market phenomenon and pricing anomaly that he observed in the Dow Jones Industrial Average stock index and documented his findings in his book "Why You Win Or Lose: The Psychology of Speculation" in 1930. His explanation for unusually high and frequent declines in stock prices on Mondays comprises the assumption that individual investors are typically greedy and vain and thus exhibit a natural propensity to sell stocks and that everyday life situations reinforce this tendency. Such everyday life situations could comprise a wife who advises her (stock market participating) husband to sell his stocks so that he stops worrying about them after she sees him with a gloomy and 'what's-the-use' expression starring at the stock page on his day-off on Sunday (Kelly, 1930). Also ordinary demands of relatives like a request from his children at college who ask for additional money or a dialogue with his mother who reminds him that some furniture has to be replaced could explain the Monday decline in DJIA stock prices since the straightforward (and maybe only) way he sees to meet all these financial demands is selling stocks (Kelly, 1930). Although Kelly's observations give great insight into the average human being's behaviour in the context of buying and selling stocks, his behavioural explanation on the weekend effect lacks a statistical test to establish a causal link between investor behaviour and stock market returns.

Shortly after Kelly's documentation of the Monday effect, the first academic study/ research paper regarding day-of-the-week effects in the context of stock returns was published in 1931 by M.J. Fields, who examined the in those times prevalent and popular Wall Street assumption that "the unwillingness of traders to carry their holdings over the uncertainties of a weekend leads to a liquidation of long accounts and a consequent decline of security prices on Saturday" (Fields, 1931). Since Saturday was a working day and US stock exchanges were open back then, the author conducted a research approach that comprises the comparison between Dow-Jones index closing prices on Saturdays and the arithmetic mean of Friday and Monday index closing prices. The statistical results indicate that the widespread assumption of an inferior DJIA performance on the day before the holiday does not seem to hold from an empirical perspective. In fact, Fields (1931) documented that the number of cases in which the DJIA index closing price on Saturday was significantly higher than the arithmetic mean of the Friday and Monday index closing price is considerably greater than the number of cases in which Saturday index closing prices were lower than the mean of Friday and Monday index closing prices. Supplementary analyses further reveal that Saturday index closing prices are both more often higher than Monday index closing prices alone and even more often higher than Friday index closing prices alone. Adapting Field's findings on a five-day working week, one could expect Friday returns to be higher than Monday and Thursday returns. The statement that Friday returns are higher when compared directly to Monday returns encompasses a research question that is examined in the later presented empirical analysis.

2.2. The weekend effect – modern findings

Frank Cross was among the first who raised academic interest in regards to the weekend effect after publishing his findings in 1973, which confirmed previous discoveries that Monday (Friday) stock returns tend to be inferior (superior) to returns on any other day of the week. His empirical analysis reveals that on Fridays, the percentage of times the hitherto unexamined S&P Composite Index advanced between 1953 and 1970 adds up to 64% whereas on Mondays, the percentage of times the stock index advanced amounts to only 39.5% (Cross, 1973). Also, Cross (1973) documented that the mean percentage change in the examined sample period of S&P stock prices between 1953 and 1970 was 0.12% on Fridays compared to -0.18% on Mondays. Furthermore, Cross (1973) provides statistical evidence that S&P Monday returns and preceding Friday returns tend to feature a positive correlation as he shows that the percentage of times the S&P index advanced on Mondays amounts to 48.8% following an advance on the preceding Friday and only lies at 24% following a decline on the previous Friday. Thus, the mean percentage index performance change on Mondays is quantified at -0.001% after an advance on the preceding Friday and -0.48% after a decline on the previous Friday.

2.2.1. The prior weekday effect

Based on Cross' (1973) finding of a positive relation between Friday and subsequent Monday returns for the S&P Composite index, subsequent studies that likewise examined correlations between chronologically related weekdays are able to confirm prior observation by Cross (1973) and refer to this anomalous regularity in stock returns as the prior weekday effect or previous weekday effect (i.a. Keef & Zhu, 2009; Bessembinder & Hertzel, 1993; Abraham & Ikenberry; 1994, Jaffe et al., 1989).

This positive correlation in stock returns between Monday and preceding Friday has shown to be unusually large and strongest compared to correlations between any other weekdays as documented by several researchers including Abraham & Ikenberry (1994), who found that negative Monday returns follow negative Friday returns in nearly 80% of the cases with a mean Monday return of -0.61%. In case of a positive return on Friday, the subsequent Monday return is positive in more than half of the cases with a mean return quantified at 0.11% (Abraham & Ikenberry, 1994). Furthermore, the authors show that this relationship tends to be most pronounced among small- and medium-sized companies. The authors attribute their findings to the trading behaviour of individual investors who tend to be more active sellers on Mondays to satisfy liquidity needs compared to institutional investors and that positive (negative) previous weekday returns reduce (increase) their selling pressure on Mondays. Additionally, the authors find that individual investors appear to be more sensitive to bad news announcements/ publications on Fridays after the stock market closes compared to institutional investors. The authors attribute their findings to the information-processing hypothesis, which claims that investors tend to postpone the collection and processing of information that arrives during the week to the weekend for time reasons as well as due to increased mental costs of collecting and processing this information. Consequently, the Monday decline in stock prices reflects delayed trading decisions, or more precisely sell transactions, predominantly by individual investors according to Abraham & Ikenberry (1996).

However, two subsequent studies found that the information-processing hypothesis is more consistent with institutional trading as compared to individual trading (Sias & Starks, 1995; Brockman & Michayluk, 1998). According to Brockman & Michayluk (1998), individual investors tend to base their Monday trading decisions rather on the returns of stocks that they individually hold than on the return of a portfolio of stocks like a stock index. The authors assume that if the previous Friday return of single stocks held by individual investors is positive, they are unlikely to sell stocks on the following Monday even though the Friday return of the corresponding stock index was negative. On the other hand, institutional investors are more likely to condition their Monday buy or sell transactions on the previous Friday rate of return of baskets of stocks like indices or portfolios. Subsequent analyses with a clear distinction of investor groups regarding the prior day effect reveal that there indeed is a negative correlation between Friday individual stock returns and Monday individual stock returns while portfolio returns between Friday and Monday feature a positive correlation, which drives or even constitutes the prior weekday effect. Consequently, Brockman & Michayluk (1998) provide statistical evidence that positive feedback trading of institutional investors contributes to the weekend effect, which further complicates this puzzling market anomaly.

In an international context, Keef et al. (2009) find that the prior weekday effect regarding Monday returns tends to be most prevalent among developing countries at the beginning of the examined sample period in 1994 and also that this positive correlation between Friday and subsequent Monday returns declined over time and essentially disappeared by 2006. Subsequent analyses revealed that the prior day effect on Mondays (and also on non-Mondays) dates back to at least 1973 (Keef et al., 2009).

Further studies additionally reveal that Monday returns not only feature a positive correlation with preceding Friday returns but also exhibit a positive correlation with the average return of the whole previous week (Mehdian & Perry, 2001; Jaffe et al., 1989). Jaffe et al. (1989) ascertain that Monday returns are positively correlated with the return of the prior week as measured from second-last Friday close to last Friday close and furthermore document that this positive prior week-Monday relationship even holds after controlling for first-order serial correlation and the well-documented positive Friday-Monday correlation, especially in the case of negative prior week returns.

Bessembinder & Hertzel (1993) likewise join the ranks of researchers contributing towards discoveries of yet unknown properties of the Monday effect by providing statistical evidence of an unusually low and often negative correlation between day after a weekend (Monday) and the second day after a weekend (Tuesday), which implies a reversal of price movements.

2.2.2. Calendar time hypothesis & trading time hypothesis

French (1980) contributed to the existing body of knowledge by examining two mutually exclusive models or hypotheses that aim to explain the underlying mechanisms of the stock return generating process, namely the calendar-time hypothesis and the trading time hypothesis. According to the calendar-time hypothesis, Mondays are expected to exhibit a stock return that is three times as high as returns for other days of the week since the return generating process operates continuously and Monday returns represent a three-calendar-day investment (calculated from Friday close to Monday close). Since investors want to be compensated for the more extended holding period over the weekend, which is associated with higher risks, the calendar-time-hypothesis predicts that Monday returns are larger compared to other weekdays and therefore already provides a forecast of the magnitude and direction of Monday returns (Hawawini & Keim, 1995). The trading time hypothesis, in turn, takes up a more a more conservative position in predicting stock returns by claiming that the return generating process only operates during (active) trading time and therefore predicts that returns on each weekday during a week should be equal, on average. Consequently, Monday returns should not differ from returns on any other day of the week (Hawawini & Keim, 1995).

Even though both hypotheses are consistent with the assumption of efficient markets, an extensive body of research provides strong statistical evidence that the predictions of both hypotheses do not seem to hold from an empirical point of view. Instead of finding higher stock returns on Mondays or equally large average returns during a week, related studies, in fact, ascertain that historical returns on Mondays are often the lowest and in many cases constitute the only negative returns during a week, on average (i.a. French, 1980; Cross, 1973; Gibbons & Hess, 1981; Keim, 1983; Lakonishok & Smidt, 1988).

Intraday analyses of stock returns give tremendous and valuable insights into the formation of stock returns, especially in consideration of non-trading periods during a week like the weekend or also holidays since they allow for temporal differentiation of stock returns within single days. Related studies that conducted intraday analyses in the context of examining day seasonality in stock returns mainly compared the stock return measured from Friday close to Monday open to the stock return during Monday trading time from market open to market close. Authors of three independent studies that examined the weekend effect according to latter approach uniformly conclude that the observed negative return on Monday accrues over the weekend from Friday close to Monday open and thus is responsible for the well-documented Monday effect (Rogalski, 1984; Smirlock & Starks, 1986; Harris, 1986). Consequently, this gives a strong indication that the Monday effect indeed is a weekend-related effect. Admittedly, this finding is not consistent with the calendar-time hypothesis that would predict larger, positive returns on Mondays; however, it still confirms one underlying assumption of this hypothesis that the return generating process does not end after market close on Fridays and continues in a direction contrary as to that predicted over non-trading periods.

Accordingly, French (1980) ascertains that both alternative models that try to explain the stock return generating process are not able to explain his findings on the anomalous daily return pattern of the S&P index in the sample period between 1953 and 1977. During each of the five five-year periods tested in his empirical analysis, French (1980) documented that the average return on Mondays was significantly negative compared to the positive average return on any other weekday is this sample. Further analyses regarding daily S&P stock market returns after holidays indicate that average negative return on Monday is rather driven by a weekend effect thus due to the weekend itself and not by a general closed-market effect (French, 1980). French (1980) provides a possible explanation for the observed persistent and significantly negative returns on Mondays being that public companies tend to release unfavourable information after the stock market close on Friday to avoid panic selling and giving investors the possibility to digest negative company news over the weekend. Under the efficient market hypothesis, rational investors should anticipate this company behaviour and discount stock prices throughout the week; however, French's (1980) findings indicate that investors are not entirely rational and stock markets indeed suffer from inefficiencies.

2.2.3. Rational explanations for the weekend effect

The existing body of knowledge suggests several further rational explanations for the weekend or Monday effect, however, none is yet able to provide the true and genuine underlying cause(-s) for this striking market anomaly. It is likely that there is no single reason for this well-documented weekend effect, but it is the sum of the pieces that give rise to the phenomenon.

The reaction of bad news and negative company announcements after Friday trading close on the stock return of the following Monday is referred to as the information trading hypothesis and has extensively been examined in related literature following French's (1980) proposal of this mechanism as being a possible explanation for the weekend effect (i.a. Patell & Wolfson, 1982; Penman, 1987; Thaler, 1987; Dyl & Maberly, 1988; Damodaran, 1989; DeFusco et al., 1993; Connolly, 1991). Although empirical studies repeatedly verified that the effect of negative company news announcements after the stock market closes on Friday on the stock return on the following Monday is statistically significant, it is only able to explain a small portion of the Monday effect. According to Damodaran (1989), company earnings announcements are as well as dividend announcements are only able to explain 2.3% and 1.1%, respectively, of the weekend effect.

Contrary to the previously mentioned studies that examined the relationship between company news, which release in most cases can be scheduled and timed, and subsequent stock returns, Steeley (2001) took a different perspective by examining the effect of macroeconomic news publications on stock returns based on UK stocks of the FTSE100 index. Surprisingly, the author found that market-wide news arrivals are clustered on Tuesday through Thursday, leaving Monday and Friday as weekdays with significantly less macroeconomic information releases. Based on the assumption that broker recommendations are biased towards buying, and less market-wide news releases on Mondays and Fridays represent decreased trading costs or more specifically information costs for investors on these days, the author concludes that this lack of information provides the natural selling opportunity for investors, which ultimately leads to inferior returns on Fridays and Mondays.

Gibbons & Hess (1981) examine one possible rational explanation for the weekend effect by testing whether general measurement errors in the prices of securities drive the weekend effect. According to the authors, infrequently traded securities feature quoted prices that are out of date which may induce systematic biases across different weekdays. However, their analyses reveal that this possible explanation does not adequately describe their data.

Keim & Stambaugh (1984) later confirmed prior findings by Gibbons and Hess (1981) and additionally documented that further measurement-error explanations likewise are not able to explain the weekend effect. The authors assumed that positive errors in prices on Friday would tend to produce lower-than-average errors on Monday, which implies a lower and possibly negative correlation between Friday and Monday returns compared to the correlation between other successive weekdays. However, the authors ascertain that Friday-Monday returns feature the highest positive correlation during a week, which contradicts the proposed rational explanation for the weekend effect. Keim & Stambaugh (1984) further examined if a so-called specialist bias or bid-ask bias serves as a possible explanation for the Monday effect, which comprises the assumption that an employee or 'specialist' of the stock exchange often determines closing prices of securities since they involve the last transaction of that asset on that day. Therefore, closing prices do not represent 'true' prices, which are typically obtained by market orders that cross during active trading, but rather represent either the bid or the ask price depended on the specialist's decision to place a buy or a sell order, respectively, for that last transaction. By providing statistical evidence for unusually low and negative Monday returns even for OTC stock, for which they measured returns as bid price-bid price and ask price-ask price, the authors were able to rule out this specialist bias as an underlying force that drives the Monday effect.

Rational explanations that comprise a delay between trading and settlement (the actual transfer of funds) in stocks have likewise been proposed in related literature as possible drivers of the weekend effect. These explanations are all based on the assumption that the settlement period differs in their length subject to the specific weekday of the transaction. Depending on the respective stock exchange, transactions on Fridays often come along with a longer settlement period while transactions on Mondays are followed by shorter settlement periods at some stock exchanges. Combined with the assumption that a longer settlement period yields additional interest for the seller, Friday and Monday returns are predicted to be higher and lower, respectively, on average (i.a. Gibbons & Hess, 1981; Lakonishok & Levi, 1982; Dyl & Martin, 1985; Hawawini & Keim, 1995). Their studies reveal that controlling for this settlement/ clearing hypothesis, for example by adjusting the daily returns for the interest rate (Lakonishok & Levi, 1982), partially reduces the weekend effect. In summary, this rational explanation for the weekend effect is only able to explain a minor part of this market anomaly.

Chen & Singal (2003) investigated whether short sellers systematically play a role in the formation of stock prices across weekdays. The authors assume that short sellers are less likely to hold their positions over long non-trading periods like weekends and thus close their positions on Fridays and reopen them on Mondays. Subsequent analyses support latter assumption as the authors reveal that stocks with a high level of relative short interest feature a higher weekend effect compared to stocks with less short interest, which provides a further piece in solving this stock pricing puzzle.

2.2.4. Investor groups, firm size and the weekend effect

While Abraham & Ikenberry (1996) attribute the observed decline in stock prices on Mondays to an increased selling activity by individual investors on that day, a subsequent empirical study by Dubois & Louvet (1996) showed that trading volumes on Mondays are significantly lower compared to those on other weekdays. The authors attribute this observation to the trading behaviour of institutional investors who are less active in buying stocks on this day. Consequently, the authors postulate that the inelasticity of demand constitutes a valid reason for the observed unusually low or even negative rates of return on Mondays (Dubois & Louvet, 1996).

Further studies that examined the Monday effect based on the trading behaviour of specific investor groups with a usual distinction between unsophisticated, individual investors and institutional investors indeed found that both investor groups are somehow responsible for the commonly observed decline in stock prices on Mondays. Respective research papers reveal that individual investors directly contribute to the Monday effect by increasing their trading activity (especially sell transactions) while institutional investors indirectly contribute to this market anomaly by their absence and thus reduced liquidity in the market (i.a. Chan et al., 2004; Brooks & Kim, 1997; Lakonishok & Maberly, 1990).

As previously mentioned, Abraham & Ikenberry (1994) additionally ascertain that the weekend effect is most pronounced among small- and medium-cap stocks compared to large-cap stocks, which they attribute to the trading behaviour of individual investors since small- to medium-sized company stocks are more likely to be traded and held by individual investors compared to large-size company stocks.

Brusa et al. (2000) ascertain a more extreme finding in regards to the relationship between weekend effect and underlying firm size as the authors observe that this market anomaly is only of existence among small firms and even reverses, thus featuring a positive Monday return, for large firms. Additionally, they find that this reverse weekend effect monotonically increases with firm size.

Harris (1986) contributes with further insight into the weekend effect-firm size relationship by revealing that the negative Monday return for smaller firms primarily accrues during the trading time on that day while a negative Monday return for larger firms mainly accrues between Friday close to Monday open thus during the non-trading period.

Gibbons & Hess (1981) additionally ascertain that Friday returns are considerably larger for indices that comprise small firms compared to indices that are mainly constituted of larger firms. However, the magnitude of the examined Monday effect - unusually low or even negative Monday returns – does not seem to be related to or affected by firm size since Monday returns turned out to be equally worse across all firm sizes.

Keim & Stambaugh (1984) later confirmed previous findings by Gibbons & Hess (1981) and likewise detect that Friday returns are negatively correlated with firm size while negative Monday returns are not affected by firm size, leaving uniformly negative Monday returns across all examined size deciles.

2.2.5. Persistence of the weekend effect

The question whether the weekend or Monday effect is persistent or rather unstable cannot be clearly answered yet as related research papers ascertain opposing findings in regards to the persistence of this market anomaly.

Connolly (1989) was among the first who explicitly examined the robustness and persistence of the weekend effect and concluded that both the weekend effect and the day-of-the-week effect in the context of US stocks seem to have disappeared by 1975, two years after their formal discovery in 1973 by Cross.

Mehdian & Perry (2001) document that the Monday effect does not seem to be structurally stable over the examined sample period from 1964 to 1998 regarding major US stock market indices. The authors consequently divided the sample into two subsamples according to the 'Black Monday' 1987 stock market crash: a pre-crash subsample from 1964 to October 1987 and a post-crash subsample from November 1987 to 1998. The authors, on the one hand, observe a 'traditional' weekend for the pre-1987 period and, on the other hand, a reversed weekend effect thus abnormally positive Monday returns for the post-1987 period.

Pettengill et al. (2003) report that the Monday effect declined over time in regards to the S&P 500 index and even reversed from featuring a negative return from 1983-1991 to exhibiting an abnormally positive return after 1991 until the end of the examined sample period in 2002.

Mehdian & Perry (2001) confirmed a prior finding by Wang et al. (1997), who both provided statistical evidence that the Monday effect primarily occurs within the last two weeks of a month while the Monday return coefficients for the first three Mondays of a month turned out to be not significantly different from zero in both papers.

More recent studies regarding the persistence of the weekend effect give further insights into the properties and dynamics of this market anomaly with Doyle & Chen (2009) reporting that the "weekday wanders in a way that must lie between a random walk and a fixed (weekday) effect" and therefore is not stationary as commonly assumed. Further extensive analyses by Olson et al. (2015) in turn support the assumption that the weekend gradually declined over time with a long-run mean reversion toward zero within their sample period from 1973 to 2013 regarding major US stock indices including Dow Jones, S&P 500 and NASDAQ.

2.2.6. Further findings & respective trading strategies

In an international context, related literature reveal that the weekend effect does not seem to be existent in some countries while others feature rather stable and considerably high Monday declines in stock prices (i.a. Hawawini & Keim 1995; Agrawal & Tandon 1994; Aggrawal & Rivoli, 1989; Dubois & Louvet, 1996).

Aggarwal & Rivoli (1989) found strong evidence that Monday represents the day with the lowest stock return during a week among three out of four examined stock markets of (at that time) emerging countries being Hong, Kong, Malaysia and Singapore.

A more recent study with a more extensive dataset by Agrawal & Tandon (1994) however observed that only nine out of nineteen mainly developed countries under study exhibit the Monday effect while Friday returns are large and significantly positive for all countries under study except of Luxembourg.

Hawawini & Keim (1995) further provide statistical evidence that the weekend effect considerably differs across countries and reveal that the Monday effect is present among countries including the USA, Canada, Germany, Japan and UK while other countries like France, Belgium, Finland or Australia do not display large and significantly negative returns on Mondays.

Further examinations of the weekend effect in an international context by Dubois & Louvet (1996) imply that the weekend effect is strong and significant for the great majority of countries under study like the USA (both S&P 500 and DJIA), Canada, Germany, UK, Hong Kong and here also for France while Australia remains unaffected by the Monday effect and Japanese markets only partly display a Monday effect.

A further research paper provides statistical evidence that a day-of-the-week effect not only appears to be existent in the return equation of stocks but also in the volatility equation as Kiymaz & Berument (2003) document. The authors ascertain that Monday features the highest volatility of returns for major stock market indices of countries like Germany and Japan while Friday represents the day with the highest volatility for countries like the USA and Canada. This outcome is in line with previous findings by Berument & Kiymaz (2001), who likewise detected that Friday features the weekday with the highest variance of returns compared to other days of the week regarding the S&P 500 index in a sample period between 1973 and 1997. Furthermore, they find that the unusually high volatility on Fridays for US stocks is most pronounced in the later part of the sample period, namely the sub-period from 1987 to 1997.

Almost 20 years earlier to latter observation, Agrawal & Tandon (1994) detected similar outcomes and find that the standard deviations of stock returns are highest on Mondays and lowest on Fridays for most of the nineteen countries under study in a sample period starting in the early 1970s for some indices and ending in the late 1980s for most examined indices.

According to the general opinion among researchers who examined the weekend effect, it is quite difficult and often impossible to economically exploit the weekend effect by pursuing trading strategies that anticipate declines and rises in stock prices on Mondays and Fridays, respectively, due to the relatively low magnitude of this market anomaly as well as due to high implementation/ trading costs.

However, studies that explicitly focused on the exploitability of market anomalies like the weekend effect find that both simple and complex trading strategies are able to enhance the risk-return trade-off. (Miller et al., 2003; Mazumder et al., 2010) Mazumder et al. (2010) demonstrated that especially a complex trading strategy performs the best while other examined, simpler trading strategies are also superior compared to a buy-and-hold strategy.

Miller et al. (2003) recognised that the often-presented argument against the exploitation of market anomalies – high transactions costs – could be ruled out by trading mutual funds that often do not feature such costs (or in some cases refund such costs). Subsequent empirical analyses reveal that simple trading rules turn out to be the most effective approach in generating superior risk-adjusted returns such as shifting money into a money market fund on Friday to avoid the negative Monday return and shifting it back into a risky mutual fund on Monday after the avoided market decline. This simple trading strategy beats a buy-and-hold strategy in terms of both returns and risks according to the authors.

2.3. Investor sentiment as a possible explanation for the weekend effect

2.3.1. Mood fluctuations during the week – psychological findings

Determining and quantifying an individual's mood state on a daily basis is challenging undertaking as direct measurements of people's mood states, for example through surveys, often only represent the subject's mood state at that exact moment of the survey taken, which is unlikely to remain stationary throughout the day. Furthermore, self-reported mood states are rather subjective, and subjects often have difficulties in reflecting their mood states in the past, which both might bias results based on such mood measurements. According to Watson (2000), one often observes “a clear disjunction between people’s beliefs and their actual affective experience” when measuring mood.

In psychological literature, mood is commonly measured along two independent dimensions being positive affect and negative affect (Birru, 2017). The independence of these two dimensions is reflected in the so-called Positive and Negative Affect Schedule (PANAS), a self-report questionnaire that is one of the most widely used instruments in the assessment of both positive and negative affect. Rossi & Rossi (1977) were among the first who identified and examined mood patterns by the day of the week by relying on self-reported surveys of students. Their evaluations of approximately 3200 responses from 82 students over a period of 40 days reveal that men’s mood tends to be more strongly affected by the day of the week compared to women’s. Besides the fact that men’s mood displays a greater variation throughout a week, the authors further document that mood states for both genders feature a clear tendency to improve throughout the week with lowest mood states at the beginning of the week that ultimately peak towards/ on the weekend. Further analyses reveal that this progressive improvement of mood during a week is mainly driven by an increase of positive affect rather than a decrease of negative affect Rossi & Rossi (1977).

A further study by McFarlane et al. (1988) that likewise relied on self-reported surveys of students measured mood according to the Affect Grid approach, which yields measures of pleasantness and arousal. Their results show that pleasantness was higher on Friday and Saturday compared to Monday while arousal peaked on Friday. However, their results do not indicate that mood was worst on Monday.

Subsequent studies that examined variation in mood throughout a week largely confirm the widespread assumption of higher mood levels on Friday (and the weekend) relative to Monday through Thursday (i.a. Larsen & Kasimatis, 1990; Reid et al., 2000).

Further analyses regarding mood fluctuations during a week with mood now being measured as positive emotions and negative emotions again confirm that rather an increase of the positive component of mood causes a positive mood state on Friday and the weekend than a decrease of the negative component of mood (Reis et al., 2000; Egloff et al., 1995). Therefore, one might conclude that it is rather the anticipation of the upcoming leisure time with family and friends that improves people’s mood towards the weekend than a two-day relief from the (possibly exhausting and stressful) workweek.

Young & Lim (2014) later documented that it is indeed the weekend or more precisely the social time that people spend on the weekend and not the workweek itself that is responsible for the observed sharp positive mood shift towards weekends. By examining and comparing mood states of both employed and unemployed individuals, the authors demonstrated that both groups, starting from different initial mood levels, feature a remarkably similar increase of the overall perceived mood on weekends. Following this, the emotional well-being decreases in similar size for both groups when the workweek begins. Their results furthermore document that both an increase of positive emotions as well as a decrease of negative emotions form this weekend high for both subject groups employed and unemployed individuals. Unlike previously mentioned studies that attributed increased positive mood states on Friday and the weekend to an increase of positive affect rather than a decrease of negative affect, Young & Lim (2014) show that the negative mood component or more precisely a decrease of negative emotions also seems to play a substantial role in the formation of the weekend high.

To put it in numbers, Helliwell & Wang (2014) ascertained that weekends offer an extra daily social time of 1.7 hours (7.1 vs 5.4 hours) which most people spend with family and friends. This extra social time consequently raises the average happiness by about 2% according to the authors. While the majority of related studies that examined daily variation in mood over the course of a week relied on data of relatively small samples that often also consisted of students only, Helliwell & Wang (2014 and 2015) on the other hand relied in both of their studies on a large representative sample of data of a telephone questionnaire from a wide-ranging US survey (Gallup/Healthways US daily poll) from 2008-2012 that comprises over 340,000 individuals. Surprisingly, the authors find that the weekend high is primarily driven by a (relatively larger) decrease of negative emotions than by a (relatively smaller) increase of positive emotions (Helliwell & Wang, 2015). Furthermore, they document that the weekend effect is twice as high for full-time workers compared the rest of the examined population and significantly smaller for employees who report that they consider their work supervisor a partner rather than a boss which implies a more satisfying and trustable work environment (Helliwell & Wang, 2015). These findings support the assumption that besides the weekend also the working days exert substantial influence on people's mood formation and variation over time. Moreover, the authors document that social time on weekends and the workplace social environment together nearly fully explain the observed weekend high for the positive emotions (and sadness) while these causes have less explanatory power for most examined negative emotions (Helliwell & Wang, 2015).

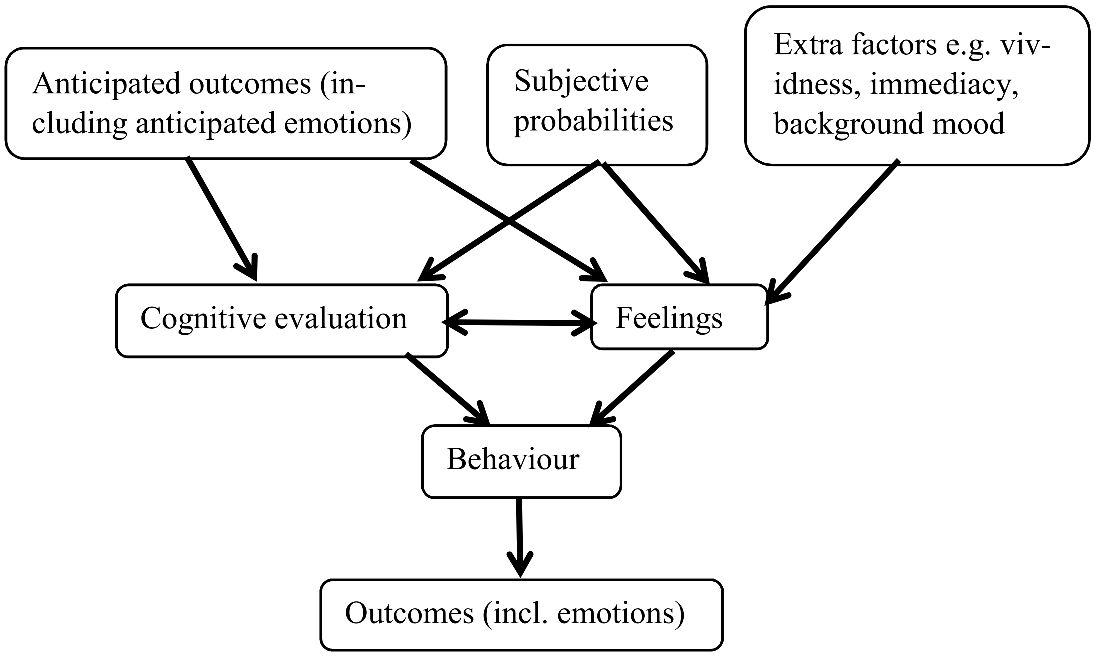
Stone et al. (2012) likewise based their analyses on data of the previously introduced wide-ranging Gallup survey and examined whether statistical proof could be ascertained for typical associations between the day-of-week and mood like the Blue Monday phenomenon by comparing the mood on Monday versus mood on Tuesday through Friday, the Thank-God-its-Friday (TGIF) association by comparing Friday versus Monday through Thursday also the positive association for weekends by comparing weekends versus weekdays. Their results show that there is no statistical evidence for the Blue Monday phenomenon while the TGIF association is statistically significant and for the most part driven by an increase of positive affect (+0.071; nearly 2/3 of the total effect) compared to a decrease of negative effect (-0.046). Analyses of mood on weekends versus weekdays reveal an even stronger overall positive increase of mood on weekends (weekend high) vs. weekdays as compared to the positive mood shift on Fridays in the TGIF analyses, which surprisingly is driven by a decrease of negative effect (-0.233) compared to an increase of positive affect (+0.195) according to the statistical results by Stone et al. (2012).

Golder & Macy (2011) gathered and analysed over 500 million public Twitter messages ('tweets') from Twitter.com to examine daily variation in mood. This approach has many advantages over the applied methods in previous studies since screening and processing tweets for words that imply positive or negative emotions yield a direct measure of mood while many other studies relied on indirect sentiment measures. Through natural language processing (NLP), constructed direct sentiment measures might reflect the mood of individuals more precisely and thus feature a higher explanatory as compared to survey-based or financial market-based (indirect) sentiment measures. First, the authors confirm the assumed independence of positive affect and negative affect which is reflected in their small correlation (r=-0.18). Their analyses reveal that the levels of positive affect (PA) are considerably higher on Saturday and Sunday compared to other weekdays while a contrary effect is less pronounced for the negative affect (NA) dimension: levels of negative affect are more condensed across days of the week, but still the lowest levels of NA are observed on Saturday and Sunday (partly also on Friday). The large dataset and their novel research approach also enable the authors to take a closer look into temporal variation in mood by conducting intraday analyses and examining hourly changes in mood. Their results indicate that positive affect features two peaks during a day: early in the morning (approx. between 6:00 a.m. and 8:00 a.m.) and around midnight. In contrast, negative affect is lowest in the morning and monotonically increases throughout the day until reaching its climax at midnight. These temporal patterns for both PA and NA are similar across all days of the week yet proceed on different levels. Furthermore, Golder & Macy (2011) examined temporal variations in mood in an international context, especially daily and weekly mood patterns in the United Arab Emirates where the traditional workweek runs from Sunday to Thursday. Their finding of a weekly mood pattern in the UAE is largely consistent with previously presented finding for western countries: the PA is higher on the weekend in the UAE (Friday-Saturday) than during the UAE workweek (Sunday – Thursday), which supports the assumption that mood rhythms are affected by sleep schedules which in turn are shaped by cultural norms.

2.3.2. Investor sentiment and financial markets

In the following, essential findings and observations on the relationship between mood and financial markets are presented in detail to get a better understanding of the interaction between investor sentiment and stock prices. Loewenstein et al. (2001) actively contributed towards understanding the human decision-making progress by formulating the risk-as-feelings model, which emphasises the importance of feelings for reaching a decision under risk and uncertainty.

Figure 2. Risk-as-feelings model
(in reference to Loewenstein et al., 2001)



According to the risk-as-feelings hypothesis, feelings play a much more prominent in the human decision-making process than the traditional economic literature suggests. At the time of the introduction of the risk-as-feelings model, the great majority of postulated theories that aim to explain the decision-making process under risk and uncertainty were based on traditional economic utility concepts (such as expected utility) and therefore consider this process from a cognitive-consequentialist perspective. However, these theories do not incorporate the above-mentioned extra factors such as vividness and most importantly, do not sufficiently account for the interaction of feelings and emotions with other relevant factors during the decision-making process. Besides the cognitive evaluation of a risky decision, individuals simultaneously consider emotions and feelings during the decision-making process, which ultimately result in a specific behaviour according to the risk-as-feelings hypothesis. Furthermore, this advanced decision-making model under risk also accounts for mood, included as an extra factor, which consequently affects feelings and emotions.

Lucey & Dowling (2005) were among the first who applied the risk-as-feeling model in the domain of financial markets and equity pricing. The authors refer to the mood-as-information hypothesis which predicts that "mood tends to inform decisions even when the cause of the mood is unrelated to the decision being made", which is labelled as mood misattribution. The phenomenon of mood misattribution has been confirmed in various experiments and surveys as for example by Johnson & Tversky (1983), which support the assumption that mood, induced by the day of the week and therefore unrelated to financial decisions, indeed affects an investor's decision-making process thus their behaviour of buying or selling stocks.

In addition, Hirshleifer & Shumway (2003) refer to mood misattribution in the sense that individuals misattribute mood induced by the current weather as relevant information when they make assessments or decisions even though individuals should not incorporate such unrelated information in their decision-making process. Therefore, weather conditions might also serve as a good and valid indirect proxy for mood that possibly is capable of predicting stock market returns, which is discussed later in this paper.

2.3.2.1. Affect infusion model & mood maintenance hypothesis

Psychological and economic literature provide two further prominent theories in regards to the processes and mechanisms on how mood influences financial risk tolerance being the Affect Infusion Model (AIM) and the Mood Maintenance Hypothesis (MMH). To put it simply, the AIM claims that people who are in a good mood have a greater risk-taking tendency compared to people in a neutral or bad mood. Consequently, a bad mood state predicts a smaller risk-taking tendency.

An opposing perspective is taken by supporters of the MMH, which basically predicts that individuals who are in a good mood tend to be less likely to take risks compared to people in a neutral or bad mood since they want to maintain and keep up their positive mood state and do not want to take risky decisions that may impair their subjective well-being. Consequently, people in a bad mood are more likely to take risky decisions to brighten up their current negative mood state.

According to a study by Grable & Roszkowski (2008), which primary objective is to determine whether either the affect infusion model or the mood maintenance hypothesis has stronger explanatory power regarding how mood influences financial risk tolerance, strong support for AIM but only regarding good mood rather than for the MMH is ascertained. Conducted related regression models reveal that people in a good mood are more likely to take risks compared to people in a neutral mood. However, the authors were not able to find a statistically significant relation between bad mood and financial risk-taking compared to neutral mood since the examined sample data comprised too few subjects in a bad or gloomy mood to verify this relation statistically. Nevertheless, their results and findings in favour of the AIM add further credence to the previously presented risk-as-feelings hypothesis and confirm that the affect attribute of mood influences an individual’s behaviour regarding risky decisions.

By an experiment designed as games with a group of regular and non-regular gamblers, Hills et al. (2001) not only were able to confirm the general predictions according to the AIM but also document that the number of risky trials played steadily and considerably increases with improving mood from depressed, neutral to happy, however, only for the non-regular subject group. This finding implies a positive relation between mood and the frequency of risky decisions as well as between mood and the persistence of risky actions.

Harding & We (2016) examined the relationship between mood states and levels of risk aversion and likewise ascertained empirical evidence for the AIM but here only regarding bad mood. The authors documented that only the negative dimension of mood state causes an increase in the level of risk aversion exhibited by males, but not by females. In light of the fact that the majority of job positions in the financial sector, especially the investment sector and asset management, are staffed by men and also that private investors for the predominant part are males, it seems plausible that this experimental finding also applies to the stock market. Latter assumption would predict that an investor's mood on Monday, which often has documented to be the worst mood state during a week, increases their risk aversion and therefore make them less likely to buy stocks, causing a decline of stock prices on that day. Analogous, a good mood on Fridays would predict increased risk-taking by investors and consequently an increased demand for stocks, causing an increase in stock prices on that day.

Previously mentioned findings and assessments might be able to explain the findings by Pettengill (1993), who showed that investors tend to take higher financial risks before the weekend and lower financial risks after the weekend.

Despite the vast body of evidence regarding the affect infusion model, some research paper determined statistical and empirical support in favour of the mood maintenance hypothesis as for example by Isen & Geva (1987) and Isen & Patrick (1983). In both papers, the authors ascertained a statistically significant relationship between positive mood and decreased risk-taking compared to neutral mood but only in the domain of low-risk situations and decisions (small stakes). For situations or decisions that involve high risks, people in a good mood, however, tend to be risk seeking compared to being in a neutral mood, which favours the AIM in this specific case.

Using the weather or more specifically 'total cloud coverage' as an indirect proxy of collective investor mood, Kliger & Levy (2003) have further examined the MMH in the context of capital markets. Their findings document that a positive (negative) mood is associated with decreases (increases) in investor's risk-taking, which is in line with predictions of the MMH.

In summary, it can be stated that the majority of related studies find stronger support and ascertain greater empirical evidence in favour of the AIM rather than for the MMH (i.a. Chou et al., 2007).

2.3.2.2. Association between mood and optimism & pessimism

Somewhat obvious, financial market participants not only rely on present factors and determinants when making financial decisions but also include (subjective) financial evaluations of possible future outcomes in their decision-making process. Since nobody can accurately forecast the future, investors rely on their subjective evaluations and predictions of future events. As per definition, optimism describes the perception or point of view of an individual who reports higher probabilities for positive future events and lower probabilities for negative future events while a pessimistic person overestimates negative events over positive events. Optimism (pessimism) generally leads to increased (decreased) risk-taking according to psychological literature and refer to this well-documented finding as optimism bias (O'Sullivan, 2015). Since the optimism bias comprises two dimension being increased probabilities for positive events and decreased probabilities for negative events, related literature find that this bias is stronger for negative events and refer to this effect as the valence effect (see f.e. Shepperd et al., 2002; Gouveia & Clarke, 2001). Consequently, an underestimation of negative events predicts the engagement in risky behaviours or generally speaking a greater involvement of risks.

Up to date, a great number of studies in the field of cognitive psychology were able to prove that mood, expressed as an emotion or feeling, and optimism, expressed as a subjective evaluation of future outcomes, are interrelated. (i.a. Wright & Bower, 1992; Sujan & Sujan, 1994; Segerstrom et al., 1998). Wright & Bower (1992) find evidence for a connection between good mood and optimism as well as bad mood and pessimism as they show that people in a good (bad) mood report higher (lower) subjective probabilities for positive events and correspondingly lower (higher) subjective probabilities for negative events. However, the association between mood and optimism/pessimism and mood works both ways: optimistic persons are more likely to be in a positive mood state as shown by Segerstrom et al. (1998).

2.3.2.3. Further findings on the investor sentiment-financial markets relation

Related literature has shown that various measures can serve as indirect proxies of investor sentiment like weather conditions such as 'total cloud coverage' by Klinger & Levy (2003) or 'sunshine' by Hirshleifer & Shumway (2003), but also soccer or other popular sports outcomes/ results can induce changes in investor mood that can be quantified as shown by Edmans et al. (2007). The authors previously stated studies provide statistical evidence that all three mentioned indirect measures of mood comprise explanatory power in predicting stock market reactions or more specifically changes in stock prices and returns.

Goetzmann et al. (2014) likewise relied on weather conditions, specifically cloud coverage, to examine the relation between weather-induced mood and US stock returns with a particular focus on institutional investors. Even though this specific group of investors is generally regarded as more sophisticated compared to private investors, the authors surprisingly find that their indirect proxy of investor sentiment is able to explain variation in prices and trading volumes of the DJIA as well as of individual stocks. They find that investor optimism, as associated with less cloud cover, increases an institutional investor's propensities to buy and also that their weather-based stock-level investor mood measure is capable of explaining daily returns of stocks that are associated with higher arbitrage costs.

A study by Schmeling (2009) revealed further interesting characteristics of the relation between investor mood or sentiment and the stock market by comparing the influence of individual investor sentiment, as measured by consumer confidence, on stock market returns across 18 highly developed countries. The author concludes that "the impact of sentiment on stock return is higher for countries which have less market integrity, less efficient regulatory institutions and which are culturally more prone to herd-like behavior and overreaction" (Schmeling, 2009).

Based on this, one might conclude that countries that feature and promote individualism, which implies less herd-like behaviour, are inhabited by investors who are less susceptible to the mood misattribution bias thus contribute less to a possible weekend effect, which will be discussed in the upcoming chapter.

2.3.3. Investor sentiment and the weekend effect

In this section, selected studies and research papers that particularly examined the relation between investor mood/ sentiment and the weekend effect are presented.

Thaler (1987) joins the rank of researchers who provide psychological or behavioural explanations for the weekend effect; however, the author did not conduct statistical tests to verify his assumptions. The author suggests that seasonal variations in investor's mood might serve as a possible explanation for the weekend effect but also refers to an unpublished working paper by Coursey & Dyl (1986), who claim that investors have "[…] a preference for compound gambles over simple gambles" (Thaler, 1987). Since investing on any weekday between Monday and Thursday can be regarded as a simple gamble as each weekday is usually followed by a trading day that allows the investor to adjust his investments or execute trades if he intends to do so, investing on Friday and holding the investment over the non-trading period, in turn, represents a compound gamble. Thus, an investor's propensity to favour compound gambles over simple gambles might be associated with higher returns on Fridays compared to other weekdays and therefore might serve as a further possible psychological or behavioural explanation for the weekend effect.

Rystrom & Benson (1989) claim that a seasonal psychological pattern or more precisely daily variation in moods, perceptions and emotions, especially a good mood and optimism on Fridays due to the upcoming weekend, and a gloomy mood and pessimism on Mondays, constitute valid explanations for the weekend effect thus higher returns of Fridays and lower on Mondays. According to the authors' perception, this psychological explanation for the weekend effect is at least as plausible as any other rational explanation suggested so far.

Despite the fact that previously mentioned studies greatly contributed towards recognising and understanding the relation between investor mood or sentiment and the weekend effect, they did not conduct empirical analyses and therefore lack of statistical evidence to verify their assumptions and conclusions.

Gondhalekar and Mehdian (2003) empirically examined the weekend effect based on NASDAQ stocks from 1971 to 2000 and applied the following indirect proxies of mood in their statistical tests: discounts on closed-end funds, returns on small stocks, consumer confidence and consumer reluctance towards buying a house. The authors concluded that the Monday effect could be explained by the blue Monday hypothesis, indicating a gloomy mood among investors that causes a reluctance to buy and a tendency to sell stocks on this specific weekday.

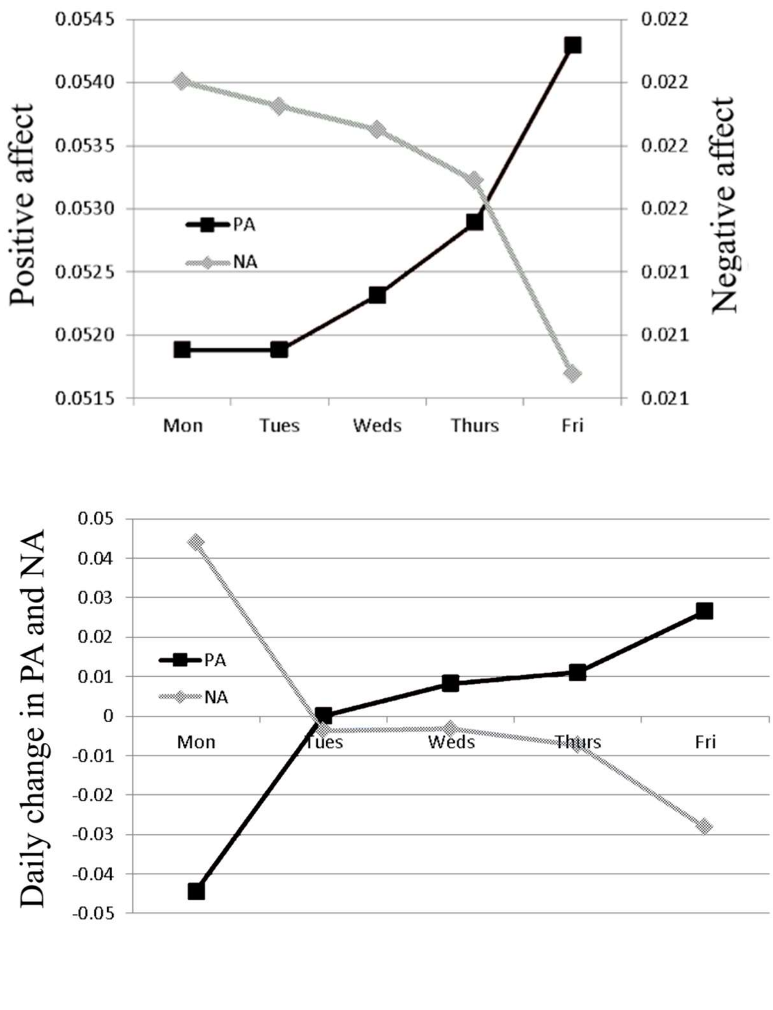
Thanks to the growing use of the internet and respective applications, the amount of exiting (and publicly available) data and information is continuously increasing, which enables researchers to construct novel and innovative direct measures of investor sentiment that have greater explanatory power and reflect investor mood or sentiment more precisely compared to indirect proxies of investor sentiment.

Bakar et al. (2014) relied on a direct measure of sentiment namely daily mood data from Facebook to examine the Monday effect across 20 international stock markets. The authors provide strong statistical evidence that the observed average negative return on Monday is largely driven by the mood of investors and further document that the Monday effect tends to disappear after controlling for mood. Bakar et al. (2014) further find that the effect of mood on the Monday effect is "[…] more prominent within small capitalization indices and within collectivist and high-uncertainty-avoidance countries." Combined with previous findings by Chui & Titman (2010), who claim that herding is more prominent among investors in collectivist countries and overreaction tends to be stronger among investors in high-uncertainty-avoidance countries, one could conclude that distortions in the investors' decision-making process such as herding or overreaction contribute to the well-documented Monday effect.

Birru (2017) significantly contributed to the existing body of knowledge regarding the weekend effect by proving novel insights into the relationship between the day of the week and the cross-section of stock returns. The author documents that speculative stocks have lower returns on Mondays and higher returns on Fridays compared to non-speculative stocks and therefore confirms a weekend effect for this subsample of stocks. While no rational explanations such as the timing of good/bad news announcements are able to explain the observed weekend effect, the author shows that behavioural explanations hold. Statistical tests reveal that a decreasing mood on Mondays leads to relatively low returns for speculative stocks on that day while an increasing mood on Fridays causes relatively high returns for speculative stocks. Birru's (2017) findings can be considered as particularly meaningful and relevant since the respective statistical analyses comprise the previously presented direct measure of mood by Golder & Macy (2011), which was constructed out of over 500 million tweets thus is quite representative and features great explanatory power in explaining the relation between mood and the weekend effect.

Figure 3. Visual representation of average positive and negative affect & respective daily changes for each weekday

This following figure visualises the average positive affect (black line) and negative affect (grey line) at the time of the market close for each weekday (upper chart) as well as daily change in PA and NA relative to the previous calendar day (lower chart) based on Twitter mood data by Golder & Macy (2011); in reference to Birru (2017).



Besides the Golder & Macy (2011) direct mood measure, Birru (2017) examined whether further indirect proxies of investor sentiment are likewise able to explain the weekend effect from a behavioural perspective. These indirect measures of sentiment include daily returns of the volatility index VIX, which represent changes in the stock market's expectation of volatility implied by S&P 500 index options and therefore serve as an indicator of fear among investors and also daily US Treasury Bill returns, which increases are associated with decreases in sentiment and can be interpreted as a "flight to safety" among investors (Birru, 2017). The respective regression outputs reveal that both indirect proxies of investor sentiment are able to at least partly explain the weekend effect as the average daily return of both the VIX and T-Bills turn out to be significantly higher on Monday compared to Friday for the subset of speculative stocks, which indicates decreases in investor sentiment on Monday compared to Friday.

Besides Birru's (2017) assessment that speculative stocks tend to be particularly prone to the weekend effect, Baker & Wurgler (2007) additionally observe that harder to arbitrage stocks are also more strongly affected by investor sentiment.

Zilca (2017) provides further interesting insights into the features and determinants of the day-of-the-week effect as he documents that this market anomaly declined over three examined sub-periods totally ranging from 1953 to 2016 and that the magnitude of the decline is greater for larger stocks compared to public companies with smaller market capitalisation. Zilca (2017) documents that "[…] the day-of-the-week effect is characterized by a pattern of monotonically improving returns during the week, but the pattern is interrupted as market capitalization increases." The proposed behavioural explanation, which implies a monotonically improving mood during a week, therefore might be able to explain the day-of-the-week effect, especially for smaller firms.

In a subsequent paper, Zilca (2017) examined the suggested behavioural explanation for the day-of-the-week effect in depth and applied an alternative and quite innovative approach being rule- and template-based pattern-recognition methods to identify and investigate patterns in stock market returns. One template that could be tested in the context of the day-of-the-week effect might be $r_{Mon} < r_{Tue} < r_{Wed} < r_{Thu} < r_{Fri}$ and subsequent analyses of this return pattern could comprise counting the number of instances where this specific rule is matched and then comparing this outcome to the expected number of instances based on randomness (Zilca, 2017).

Zilca (2017) consequently examined if mood score templates are capable of explaining a day-of-the-week effect among US stocks from 1953 to 2006. The underlying data for the applied mood score templates are drawn for one from an aged survey by Farber (1953) and for another from a prior study by the authors in 2007; however, despite the large time period of over 50 years in between the two surveys, their results are surprisingly similar. Both surveys display a monotonically increasing mood during a workweek from Monday to Friday and together with a simple and weighted average of both mood scores, the author derived four exterior mood score templates and applied them in the statistical tests.

The respective test outputs reveal that the applied mood templates have substantial explanatory power for the day-of-week-effect regarding stock returns as "between 35% and 90% of the variation of the average daily abnormal returns can be attributed to mood fluctuations throughout the week" according to Zilca (2017).

In the upcoming chapter, I present my empirical approach, which comprises analyses and statistical test that on the one hand aim to determine whether a weekend effect is present in the data under study and on the other hand intend to assess whether behavioural explanations, in particular daily changes in investor sentiment, are able to at least partly explain a weekend effect.

3. Empirical approach

In this chapter, I present my empirical approach that comprises the analysis of different perspectives on a weekend-related effect on European stock index returns, followed by an analysis of different indirect investor sentiment measures in regards to their ability to explain at least to some extent a potential weekend effect in the data under study. Subsequently, I present my outcomes of performed robustness checks based on estimates of a statistical model that accounts for heteroscedasticity and autocorrelation to validate my findings regarding the existence of a weekend effect in the data under study.

3.1. Data

To determine and examine a weekend effect as well as to test for behavioural explanations for this seasonal variation in stock returns, I rely on daily closing prices of nine national stock market indices within six European countries in a sample period from 03.01.2000 (Monday) to 30.04.2018 (Monday).

In regards to the German stock market, I include daily quotes from the following four indices: DAX (blue chip stocks), MDAX (mid-cap stocks), SDAX (small-cap stocks) and TecDAX (mid- to large-cap technology stocks). Furthermore, the dataset comprises daily closing prices of the OMX Vilnius index (Lithuania) and OMX Tallinn index (Estonia). Regarding Northern Europe, daily quotes of the OMX Helsinki 25 index (Finland), OSEAX index (Norway) and OMX Iceland 15 (Iceland) are included in my sample data.

In total, the examined dataset comprises 41,590 observations with at least 4,554, at most 4,657 and on average 4,621.1 observations per index.

Two observations have been excluded from the original dataset that initially comprised 41,592 observations being the 13.10.2008 and 09.12.2008 of the Icelandic stock index OMX Iceland 15 due to negative outliers in respect of daily returns. In virtue of the financial crisis 2008, trading at the Iceland stock exchange was suspended for the three successive trading days in October 2008 and the market value of three big banks that reflected about 73 of the total index value (as of 30.06.2018) had been set to zero, which caused the abnormal decline in index value.

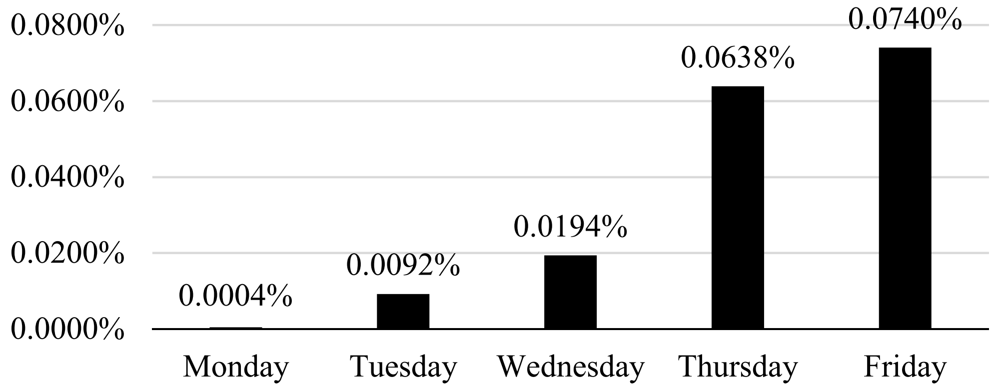
Daily quotes including opening prices, closing prices, as well as high and low prices of the examined indices were retrieved from a financial information website that in turn obtain respective quotes from the German financial data provider 'vwd Vereinigte Wirtschaftsdienste'.[2]

I specifically picked previously mentioned stock market indices to examine the weekend effect since these indices are denoted as total return indices, which makes them especially suitable for examining seasonal stock return anomalies. Total return indices measure the performance of its respective components as if all cash distributions are reinvested, which is especially relevant for dividend payments that are considered or included in the respective stock price on ex-dividend date and consequently don't negatively affect its quoted price on that day. Accounting for dividend payments is particularly important for examining weekly patterns in stock returns since stocks go ex-dividend considerably more often on Mondays compared to other days of the week, which would result in artificial negative returns on Mondays as it is the case for indices that are generally quoted as price return indices like the S&P 500 (see f.e. Fishe et al., 1993; Athanassakos & Robinson, 1994). Consequently, not adjusting for dividend payments would negatively bias returns on Mondays and might foster a type I error (rejecting of H0 even though it is true; "false positive" finding) when examining the weekend effect or more specifically the Monday effect.

[2] https://stooq.com/

The simple averages of daily returns across the whole dataset (41,590 observations) already give an indication of the distribution and characteristics of returns over the workweek in the sample period from January 2000 to April 2018.

Figure 4. Simple average of daily returns by the day of the week – all nine European stock indices from 01/2000 to 04/2018



3.2. Methodology

Related literature provides several approaches and methods for examining a potential weekend effect regarding stock returns, however, these approaches largely differ in their applied method of quantifying of this market anomaly. Since the weekend naturally constitutes the end of a calendar week, the examination of a possible weekend-induced effect on stock returns requires a particular focus on the stock market returns on days surrounding the weekend, namely Friday and Monday. As reported in the previous related literature section, returns on days directly before and directly after the weekend are most affected by a weekend-related effect, which is often reflected in superior returns on Fridays and inferior returns on Mondays. These two assumptions constitute and reflect the two components of the weekend effect.

In this paper, the weekend effect is examined based on the null hypothesis that stock returns do not substantially differ on average during a week. This assumption of no differences in daily returns between weekdays gives the following null hypothesis:

H0: $Return_{Mon} = Return_{Tue} = Return_{Wed} = Return_{Thu} = Return_{Fri}$

To examine the weekend effect statistically, I rely on the following four approaches: First, I compare the returns on Mondays and Fridays each to the respective returns on the other four weekdays. This yields the first alternative hypothesis **H1**, which states that Monday returns are lower compared to Tuesday to Friday returns and Friday returns are higher compared to Monday to Thursday returns.

Second, I compare Monday and Friday returns each to Tuesday-Thursday returns. This approach gives the second alternative hypothesis **H2**, stating that both Monday returns are lower and Friday returns are higher compared to Tuesday-Thursday returns.

Third, Monday and Friday returns each are compared to Wednesday returns, which gives an idea of the difference in returns between the days surrounding the weekend and the weekday that lies in the midst of these days. Thus, returns on Wednesday might be least affected by a weekend-related effect since Wednesday constitutes the weekday with the greatest distance of time between the two weekends surrounding that weekday. This perspective on the weekend effect, in turn, yields in the third alternative hypothesis **H3,** claiming that both Monday returns are lower and Friday returns are higher compared to Wednesday returns.

Forth, I compare Monday and Friday returns directly with each other, which yields the fourth alternative hypothesis **H4**, stating that Monday returns are lower compared to Friday returns and analogous Friday returns are higher compared to Monday returns. This alternative hypothesis reflects the 'traditional' definition or interpretation of the weekend effect according to the related literature (i.a. Cross, 1973). Latter presented hypotheses H1-H4 are tested in chapter 3.3.1.

To examine behavioural explanations for the weekend effect as presented in chapter 3.3.2, I include indirect proxies of investor mood/ sentiment as meditating variables into the regressions with a similar model specification as tested in H4 to explore the underlying mechanism between the day of the week and stock returns. These indirect proxies of investor sentiment include daily returns of the volatility indices VSTOXX and VDAX, daily returns of the gold future prices at the commodity exchange denoted in USD and EUR as well as average daily returns of German government bonds with durations of 10 as well as 30 years. Even though indirect sentiment measures such as daily VDAX returns or average daily returns of German government bonds are expected to reflect the daily sentiment of predominantly German-speaking investors, I expect investor sentiment not to be largely different among countries in the European area on a daily basis. Therefore, all previously outlined indirect sentiment measures are used for all nine European stock indices under study in the later presented mediation analysis in chapter 3.3.2.

In a similar way as Baker & Wurgler (2007) and Birru (2017), who relied on the daily returns of the VIX index to measure investor sentiment, I rely on daily return data of the VSTOXX and VDAX to measure investor sentiment in the sense of an investor fear gauge in a European context. In regards to the weekend effect, expect daily returns of the VSTOXX and VDAX to be higher on Mondays compared to these on Fridays, which reflects decreases in sentiment on Mondays and increases in sentiment on Fridays. Since the VSTOXX and VDAX measure the expected volatility for the next 30 days of their underlying stock index EURO STOXX 50 and DAX, respectively, one could argue that increases (decreases) in respective volatility indices reflect increases (decreases) in fear or tension among market participants. Since Monday is often associated with negative emotions while Friday is associated with positive emotions as shown in the previous chapter, it seems plausible that daily changes in the VSTOXX and VDAX are able to capture negative emotions among investors and thus serve as a behavioural explanation for the weekend effect.

As Baker & Wurgler (2012), Da et al. (2014) and Birru (2017) show, times of high sentiment are associated with relatively low demand for safe assets such as treasury bonds or investments in gold. Therefore, respective daily return data of such assets could serve as suitable investor sentiment measures since increases in bond and gold returns reflect increases in the demand of these assets and therefore a 'flight to safety' or 'flight to quality' from an investor's perspective, which, in turn, is associated with decreases in investor sentiment. In my empirical analysis, I for one include the average daily returns of 10-year and 30-year German government bonds and for another daily return of gold future prices denoted in EUR and USD to construct investor sentiment measures. In regards to the weekend effect, I expect that daily returns of previously mentioned assets that are considered as safe and of high quality to be higher on Mondays compared to these on Fridays, which reflects decreases of investor sentiment on Mondays and analogous increases of sentiment on Fridays. If investors prefer safe and quality assets to risky assets such as stocks, one could argue well that this increased demand for such assets reflects risk-avoidance due to caution or scepticism or possibly also due to anxiety or fear among investors. It seems plausible that these emotions and sentiments are most pronounced on days surrounding the weekend compared to Tuesday-Thursday and thus could serve as a behavioural explanation for the weekend effect.

The inclusion of previously mentioned indirect proxies of investor sentiment in respective fixed effects regressions constitute the following additional alternative hypotheses tested in this paper in the context of examining behavioural explanations for the weekend effect:

H1b: Daily returns of the volatility indices VSTOXX and VDAX are valid and statistically significant mediator variables for the weekend effect as tested in H4 and by reflecting changes in investor sentiment, they serve as a behavioural explanation for this association.

H2b: Average daily returns of 10-year and 30-year German government bonds are valid and statistically significant mediator variables for the weekend effect as tested in H4 and by reflecting changes in investor sentiment, they serve as a behavioural explanation for this association.

H3b: Daily returns of gold future prices denoted in USD and EUR are valid and statistically significant mediator variables for the weekend effect as tested in H4 and by reflecting changes in investor sentiment, they serve as a behavioural explanation for this association.

These three alternative hypotheses in the context of examining behavioural explanations for the weekend effect refer to the tested second null-hypothesis **H0b,** which claims that the applied indirect proxies of investor sentiment do not serve as valid mediator variables for weekend effect as tested in alternative hypothesis H4 and thus are not able to explain this market anomaly from a behavioural point of view. Invalid mediation is the case if the respective coefficient of the included mediator variable in the final mediation model is not statistically significant and/or the negative relation between the Monday dummy and logarithmic returns is still present and remains statistically significant (Friday as reference category). The conducted mediation analyses are based on a three-step mediation testing approach by Baron & Kenny (1986), which is presented in detail in chapter 3.3.2.

The structure of the dataset as longitudinal data obviously makes panel regressions the most suitable approach to examine coherences between the day of the week and stock returns within the nine stock indices under study. I rely on fixed effects models in the later presented analyses since these models allow to control for (or rather eliminate) entity-specific factors that cannot be observed or measured and which may influence or bias the predictor or outcome variables. By removing these time-invariant individual characteristics, the net effect of the predictors on the outcome variable can be assessed. One example of such entity-specific factors could be the composition of the examined stock indices or more precisely the distribution and share of specific industries within the indices. It seems plausible that stock indices such as the TecDAX, which reflects the thirty largest technology companies in Germany, feature a different return pattern as compared to indices such as the DAX with a more balanced composition of industries. Since the composition of stock indices more or less remains constant over time, cycles of increased or decreased demand for stocks of a specific industry is reflected in the stock indices' daily returns, especially for indices that are dominated by specific industries, which ultimately might bias the results and thus should be controlled for.

From an econometric perspective, the applied approach involves running regressions of a measure of index returns of index i on day t on k time-varying explanatory variables on day t, which include dummy variables for the examined weekdays as well as further selected determinants of index returns in period t, hereinafter referred to as control variables. The number of applied independent/ explanatory variables in the later presented models is denoted by $k = 1, \dots, K$.

In the following passage, the logarithmic index return for index i at time t as the dependent variable is denoted by $y_{i,t}$ and all explanatory variables are jointly denoted by the time-variant $1 \; x \; K$ regressor matrix $\boldsymbol{X}_{i,t}$ along with the respective $k + 1$ coefficients vector denoted by $\boldsymbol{\beta}$.

The applied approach starts from a linear unobserved effects model for $N = 46{,}075$ daily observations across nine groups (indices), representing between 4,483 and 4,657 observations per index (which corresponds to respective time periods T) with the equation:

$$y_{i,t} = \boldsymbol{X}_{i,t}\boldsymbol{\beta} + a_i + u_{i,t} \text{ for } t = 1, \dots, T \text{ and } i = 1, \dots, N$$

where a_i is the unobserved time-invariant individual effect and $u_{i,t}$ is the error term. Fixed effect models eliminate the unobserved a_i by demeaning the variables or more precisely, by subtracting the respective means over time from the variables.

This $within$ transformation of the applied fixed effects models can be formulated as follows:

$$y_{i,t} - \overline{y_\iota} = \left(\boldsymbol{X}_{i,t} - \overline{\boldsymbol{X}_\iota}\right)\boldsymbol{\beta} + (a_i - \overline{a_\iota}) + (u_{i,t} - \overline{u_\iota})$$

$$\text{where } \overline{\boldsymbol{X}_\iota} = \frac{1}{T}\sum_{t=1}^{T}\boldsymbol{X}_{i,t} \;\; and \; \overline{u_\iota} = \frac{1}{T}\sum_{t=1}^{T}u_{i,t}$$

Since the unobserved individual-specific heterogeneity a_i is constant, $\overline{a_\iota} = a_i$ which accordingly eliminates the "fixed effect". This transformation consequently leads to the following equation:

$$\ddot{y}_{i,t} = \ddot{\boldsymbol{X}}_{i,t}\boldsymbol{\beta} + \ddot{u}_{i,t}$$

The fixed effects (or within group) estimator and K-vector $\widehat{\boldsymbol{\beta}}_{FE}$ is finally obtained by a pooled ordinary least squares (OLS) regression of $\ddot{y}$ on the $1 \; x \; K$ regressor matrix $\ddot{\boldsymbol{X}}$.

To produce standard error estimates that are correctly sized and robust to disturbances being heteroscedastic or autocorrelated, I rely on an appropriate standard error computing approach for the conducted fixed effects regressions that is clustering standard errors by index.

Since the inclusion of month dummies in the fixed effects regressions does not increase the predictive power of the applied models as the magnitude of the coefficients of interest as well as their statistical significance only minimally changes after controlling for month effects, fixed effects models without the adjustment for time effects are presented in this paper. For comparison reasons, the regression outputs of the fixed effects models including month dummies are presented in table 12 in the Appendix.

In regards to the applied variables in the fixed effect models, I created different measures that reflect the indices' daily returns and dummy variables that indicate the day of the week. Additionally, I created control variables that for one reflect the daily volatility in index prices and for another reflect daily changes in the USD/EUR exchange rate, which both might affect index prices. Furthermore, I computed daily return measures of implicit volatility indices, German government bonds and gold future prices that might be able to reflect investor sentiment and therefore serve as behavioural explanations for the weekend effect.

Measures of daily index returns as the dependent variable in the upcoming fixed effects models are constructed as follows:

$$rawreturn_{i,t} = \frac{closing\ price_{i,t}}{closing\ price_{i,t-1}} - 1$$

$$logreturn_{i,t} = log(\frac{closing\ price_{i,t}}{closing\ price_{i,t-1}})$$

The ordinary return measure rawreturn reflects the arithmetic daily return of an index while the variable logreturn measures the logarithmic daily return of an index. Both return measures are approximately equal when returns are small but their difference in calculated return values increases as the difference between index closing price at day t and closing price at day t-1 increases both for negative and positive returns. Nevertheless, logarithmic returns bear a significant advantage over arithmetic or ordinary returns by being symmetric while ordinary returns are not. This characteristic difference between both measures is reflected in the following example: an arithmetic return increase of +50% of a 100 Euro investment, followed by a decrease of -50%, yields a final value of 75 Euro while a logarithmic return increase and subsequent decrease of +50 and -50%, respectively, results in a final value of 100 Euro, equal to the initial investment.

Control variables included in later presented fixed effects models comprise an alternative measure of the daily stock price volatility defined as hlmean as well as the daily change of the USD/EUR exchange rate, defined as USDEURchange.

The variable hlmean puts the difference between today's high and today's low (index price) in relation to the respective mean weekly closing price of that specific index and is denoted as follows:

$$hlmean_{i,t} = \frac{(high\ price_{i,t} - \ low\ price_{i,t})}{mean\ weekly\ closing\ price_{i,t}}$$

I expect the control variable hlmean to be negatively correlated with daily stock index returns as increases in this stock price volatility measure translates into a greater fluctuation in intraday index prices, which is associated with increases in uncertainty and risk. Ultimately, increased risk and uncertainty should generally lead to lower index returns.

In regards to the applied control variable USDEURchange, I expect the USD/EUR exchange rate to be positively correlated with daily returns of European stock indices as increases in the euro rate translates into depreciations of the Euro currency, which makes investments in European stocks or indices more appealing and profitable for non-Euro investors. The resulting increased demand for European assets by non-Euro investors ultimately should lead to higher prices of European assets thus increased returns of the European stock indices under study.

The control variable USDEURchange as well as the previously introduced indirect proxies of investor sentiment being the daily return of gold future prices at the commodity exchange denoted in EUR and USD (goldeurreturn and goldusdreturn, respectively), daily returns of the volatility indices VSTOXX and VDAX (vstoxxreturn and vdaxreturn, respectively) as well as the average daily return of a blend of German government bonds 'Bunds' with a duration of 10 years and 30 years (bund10return and bund30return, respectively) are all calculated according to the ordinary arithmetic return formula:

$$return_{i,t} = = \frac{closing\ price_{i,t}}{closing\ price_{i,t-1}} - 1$$

In-depth examinations of the longitudinal dataset reveal that the data under study feature linear heteroscedasticity and display serial correlation, i.e. autocorrelation. Based on the assumption of normally distributed errors, the Breusch-Pagan test (1979) and Cook–Weisberg test (1983) for heteroscedasticity indicate that the variance of the errors in a OLS regression of the index return series on the applied independent variables including weekday dummies is not constant and therefore is heteroscedastic. The respective outputs of the conducted tests for heteroscedasticity are displayed in table 13 in the Appendix. In the case of conditional heteroscedasticity regarding the error process, many popular autocorrelation tests like the Box-Pierce test (1970), the refined Ljung-Box test (1978) and the Breusch-Godfrey test (both 1978) are not applicable for testing serial correlations. However, the Cumby-Huizinga (1992 and 1990) general test for autocorrelation reveals that daily returns display a serial correlation at lag order 1. The respective outputs of the conducted tests are likewise presented in table 13 in the Appendix. To account for the detected heteroscedasticity and first-order autocorrelation, I fit a GARCH(1,1) model to the data. This generalised autoregressive conditional heteroscedasticity (GARCH) model is especially suitable for modelling the financial time series under study that feature time-varying volatility and volatility clustering. The GARCH model consists of two components, an ARCH term and a GARCH term. The GARCH(p,q) model was first introduced by Bollerslev (1986) and was developed based on the ARCH model proposed by Engle (1982). The GARCH model can be regarded as an extension or generalisation of the original ARCH model since it assumes an autoregressive moving average model (ARMA) model for the error variance. The ARMA model yields the conditional mean/ standardised residuals of the examined return series while the GARCH model specifies the conditional variance of the return series. In other words, the conditional mean of the process is modelled as ARMA whereas the conditional variance is modelled as GARCH. A GARCH(1,1) model is a specification of the general GARCH(p,q), where p defines the order of the GARCH terms σ^2 and q represents the order of the ARCH terms ϵ^2.

For a GARCH(p,q) model, the following restriction applies: if the input argument is specified as $p > 0$, then $q > 0$ has to be specified. For $p = 0$, the GARCH(p,q) model is equivalent to an ARCH(q) model. Consequently, I set the number of lagged squared innovations (ARCH terms) $q = 1$, which gives the GARCH(1,1) model specification:

$$\sigma_t^2 = \alpha_0 + \alpha_1 X_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

where $\alpha_0 > 0,\ \alpha_1 > 0, \beta_1 > 0\ and\ \alpha_1 + \beta_1 > 0$

The term σ_t^2 represents the conditional variance in returns at time t, X_{t-1}^2 represents last period's squared return, σ_{t-1}^2 represents last period's variance in returns and α_0, α_1 and β_1 represent coefficients. Therefore, the forecast of the variance in returns for the next period is a blend of last period's squared returns and last period's

variance in returns. In other words, the future variance is predicted based on its own past and the past of the time series (→ conditional variance).
The parameter X_t^2 is derived from an ARMA(1,1) model.
The ARMA(1,1) model is denoted as follows:

$$X_t = c + \varepsilon_t + \varphi_1 X_{t-1} + \theta_1 \varepsilon_{t-1}$$

where X_t represents the conditional mean in returns at time t, X_{t-1} represents last period's return, c is a constant, ε_t and ε_{t-1} represent white noise error terms, φ_1 and θ_1 represent parameters of the model.
The lag length p = 1 for the applied GARCH(p,q) model has been established by an examination of serial correlations for up to four lags by conducting the previously mentioned Cumby-Huizinga (1992 and 1990) general test for autocorrelation, which indicated first-order autocorrelation (see table 13 in the Appendix).
The respective parameters being the residuals (conditional means of index returns) and the conditional variances of the applied GARCH(1,1) model were estimated separately for all nine indices under study by the Maximum-Likelihood method.
The model parameters were estimated based on a Gaussian innovation distribution since the Akaike information criterion (AIC), and Bayesian information criterion (BIC) both reveal that the estimated model with Gaussian distribution fits the data better than a model with a Student's t distribution in regards to the innovation distribution. This estimated residuals (conditional means) and conditional variances of daily returns for each of the nine indices under study have been computed based on the logarithmic daily return measure (logreturn). GARCH(1,1) model parameter estimates (residuals and conditional variances) based on logarithmic returns are employed in the fixed effects models presented in section 3.3.3 of this paper in the context of robustness checks.
GARCH models have been increasingly popular in analysing time-series of stock returns since they do not assume a constant variance but a time-varying variance in stock returns and therefore might be able to provide more robust and meaningful insights into the weekend effect compared to traditional econometric approaches (see f.e. Zhang et al., 2017; Dolye & Chen, 2009; Kiymaz & Berument, 2003; Herwatz, 2000).
Conolly (1989 and 1991), who examined the robustness of the weekend effect for one in regards to its temporal persistence and for another regarding different estimation methods, points out that results and estimates largely differ depending on the applied statistical test. The author documents that fitting a GARCH model to the data predicts only weak statistical evidence of a weekend as compared to

ordinary OLS regressions without fitted data in which the variance in stock returns is assumed to be constant and a weekend effect is estimated to be statistically significant and higher in magnitude (Connolly, 1989). Therefore, I present fixed effects models based on estimates of a GARCH(1,1) model parameter estimates to examine the robustness of the weekend effect in chapter 3.3.3.

In the following chapter, I first present the outcomes of the weekend effect analysis where I examine whether a weekend effect regarding index returns is of existence in the data under study, followed the analysis of behavioural explanations for the weekend effect. Finally, I conduct robustness checks to verify prior findings of the weekend effect analysis by running fixed effects regressions on computed estimates of an GARCH(1,1) model.

Table 1. Summary statistics

The following table presents summary statistics of all applied variables in the performed fixed effects regressions throughout this paper.

variable	**N**	**mean**	**p50**	**min**	**max**	**sd**	**cv**	**p25**	**p75**
rawreturn	41590	0.0003332	0.0007076	-0.1597381	0.1567676	0.013569	40.72296	-0.0051352	0.0063632
logreturn	41590	0.0002409	0.0007073	-0.1740416	0.1456295	0.0135925	56.41913	-0.0051484	0.006343
GARCH_Residual	41590	-0.0004179	0.0000521	-0.1745228	0.1451484	0.0135927	-32.5293	-0.0058011	0.0056718
GARCHcondVar	41590	0.000193	0.0001212	0.0000214	0.0098756	0.0002859	1.481554	0.0000758	0.0002222
hlmean	41590	0.0133143	0.0100439	0	0.1884025	0.0122322	0.9187279	0.0061272	0.0167229
vstoxxreturn	41590	0.0016872	-0.0043711	-0.3525513	0.6004826	0.0621013	36.80725	-0.0345709	0.0303498
vdaxreturn	41590	0.0013076	-0.0020601	-0.3092783	0.5080918	0.0549529	42.02724	-0.0313707	0.027759
bund10return	41590	0.0000549	0.0000766	-0.049872	0.0591895	0.0036744	66.92981	-0.0016656	0.0018753
bund30return	41590	0.0001128	0.0001967	-0.0632107	0.0740243	0.0057194	50.69376	-0.0029516	0.0032194
goldusdreturn	41590	0.0003962	0.0004091	-0.0879506	0.1143954	0.0113365	28.6165	-0.0050233	0.0063089
goldeurreturn	41590	0.0003486	0.0003001	-0.08348	0.098471	0.0107912	30.95366	-0.0049484	0.0056903
USDEURchange	41590	-0.0000116	-0.0001285	-0.0335072	0.0299162	0.0063321	-544.1011	-0.0036071	0.0037213

Note: the variables GARCH_Residual and GARCHcondVar were derived from a GARCH(1,1) model with Gaussian innovation distribution based on daily logarithmic returns (logreturn).

3.3. Main results and robustness checks

This paper's main objective is to examine whether daily returns of nine European stock indices are affected by the day of the week in a way that returns on Friday and Monday are higher and lower, respectively, on average and if true, to test whether behavioural explanations namely investor sentiment is able to explain this market anomaly. The existence of a weekend effect in the dataset under study is analysed from different perspectives as stated by the alternative hypotheses H1 to H4. The traditional weekend is examined according to the alternative hypothesis H4, which comprises the direct comparison between Friday and Monday returns. The findings of the weekend effect analysis is outlined in chapter 3.3.1

Results of the mediation testing approach based on the statistical model used for alternative hypothesis H4 with the involvement of indirect proxies of investor sentiment being daily volatility index returns (H1b), average daily German government bond returns (H2b) and daily gold future returns (H3b) as behavioural explanations for the weekend effect are presented in chapter 3.3.2. Furthermore, I present separate mediation and effect paths analyses according to SEM to validate the mediation of investor sentiment measures on the weekend effect.

All fixed effects regressions presented in chapter 3.3.1 and 3.3.2 are based on the logarithmic return measure as the dependent variable since the comparison of regression outputs between log-returns and raw-returns indicate that the logarithmic return measure does a better job in capturing interferences between the day of the week and index returns. However, interferences and conclusions according to fixed effects regression based on raw-returns only slightly differ to these presented in the upcoming chapter.

For reasons of clarity and comprehensibility, the statistical results of all performed analyses in chapter 3.3 are displayed at the end of this chapter. The detailed results of the conducted fixed effects regression including coefficients, standard errors, t-values and p-values of all applied variables are presented in the Appendix.

3.3.1. Analysis of the weekend effect

The respective regression outcomes regarding the weekend effect analysis are presented in table 2 at the end of chapter 3.3.

By examining the weekend effect through different lenses as stated in the alternative hypotheses H1-H4, I aim to provide statistical evidence whether Friday and

Monday returns are significantly different compared to the respective reference categories under study (H1-H3) as well as significantly different when compared directly to each other (H4).

To examine hypotheses H1-H4, I conduct fixed effects regressions of the logarithmic return on respective dummy variables that reflect the day of the week while controlling for the daily USD/EUR exchange rate change, a variance proxy being the variable hlmean and the logarithmic return at time t-1 (logreturnyesterday) to account for the detected first order autocorrelation. The conducted fixed effects regression models can be formulated as follows:

$$logre\ddot{t}urn_{i,t} = \ddot{\boldsymbol{X}}_{i,t}\boldsymbol{\beta} + \ddot{u}_{i,t}$$

where the regressor matrix $\ddot{\boldsymbol{X}}_{i,t}$ comprises the variables USDEURchange, hlmean, logreturnyesterday as standard features and respective dummy variables that reflect the day of the week dependent on the tested alternative hypothesis. Dummy variables of the following weekdays are included in the respective fixed effects regressions within the scope of testing alternative hypotheses H1-H4: Monday (Panel H1-1) and Friday (Panel H1-2), both Monday and Friday (Panel H2), Monday, Tuesday, Thursday and Friday (Panel H3) and Monday, Tuesday, Wednesday and Thursday (Panel H4-1). Panel H4-2 comprises weekday dummy variables from Tuesday to Fridays thus sets Monday as the reference category, which obviously yields the same coefficients for the Monday-Friday return relationship as estimated in Panel H4-1. Nevertheless, the regression results in Panel H4-2 give an idea about the relationship between returns on Monday and other weekdays and therefore are shown for comparison reasons.

According to alternative hypothesis H1, a weekend effect is of existence in my data if Monday returns are significantly lower compared to Tuesday to Friday returns and Friday returns are significantly higher compared to Monday to Thursday returns. A look on the coefficient of the Monday dummy variable in the fixed effects model output reported in Panel H1-1 gives indication that Monday returns are lower compared to Tuesday-Friday returns due to its negative sign; however, this findings is not statistically significant at the 5% level as a p-value of 0.0611 implies. Furthermore, the magnitude of a hypothetical Monday effect is rather small and translates into a decrease of only approximately 0.042% in daily index returns on Monday compared to Thursday-Friday, ceteris paribus. Control variables being daily USD/EUR exchange rate changes (USDEURchange) as well as the alternative daily index return volatility measure (hlmean) have predictive power in the first Panel H1-1 by featuring coefficients that are statistically significant at the 5% level and

0.1% level, respectively, and are negatively correlated with daily logarithmic index returns. A negative relation between the daily index volatility measure and daily logarithmic index returns lies within expectations; however, I expected the daily USD/EUR exchange rate to exhibit a positive rather than a negative correlation with European stock index returns. A gain of the Euro currency compared to USD makes investments in European companies less attractive for US investors, which generally should lead to decreasing prices of European stocks due to the decreased demand by non-Euro investors. Nevertheless, one explanation for the finding of a negative relation between the Euro rate and European stock index return could be that existing individual and especially institutional US investors of European stocks want to take advantage of the stronger Euro currency and thus might sell their existing investments to cash out and transfer their money back to the US. The corresponding Panel H1-2 reports the output from a fixed effects model that examines the second part of alternative hypothesis H1. The positive and statistically significant (at the 5% level) coefficient of the Friday dummy indicates that returns on Fridays are higher compared to returns from Monday to Thursday, in numbers approximately 0.044% higher, ceteris paribus. The magnitude of the effect is very small, however, it is still of existence. Overall, in the context of the first alternative H1, I cannot reject the null hypothesis at the 5% level that returns are equal during a week and conclude that a clear statistical evidence for a weekend effect cannot be established based on these two regression models.

Alternative hypothesis H2 involves the comparison of both Monday and Friday returns with returns from Tuesday to Thursday. Consequently, both Monday and Friday dummies are included in the fixed effects regression equation to examine these relationships; the regression output is displayed in Panel H2. Similar to the model outcomes for the first alternative hypothesis H1, the coefficient for the Monday dummy features a negative coefficient while the Friday dummy coefficient exhibits a positive sign. This indicates that Monday (Friday) returns are lower (higher) compared to Tuesday to Thursday returns, however, both Monday and Friday dummy coefficients are not statistically significant at the 5% level. While the coefficient of the Friday dummy features a p-value of 0.0582 and is just not statically significant at the 5% level, the Monday dummy coefficient exhibits a p-value of 0.0902 and is far from being statistically significant at the 5% level, which gives indication that index returns seem to be more strongly linked to Fridays than to Mondays.

Overall, I conclude that I cannot reject the H0 at the 5% significance level in the context of the second alternative hypothesis H2 as I am not able to find clear statistical evidence for a weekend effect based on this model specification.

Panel H3 displays the model estimates for the third alternative hypothesis H3, which implies the comparison of Monday and Friday returns with Wednesday returns as the reference category. The shown fixed effects regression output shows that Friday returns are higher compared to Wednesday returns with this findings being statistically significant at the 5% level while Monday returns do not seem to be statistically different to Wednesday returns (p-value 0.2963). As a result, I infer that the null hypothesis cannot be rejected at a 5% significance level in the context of the third alternative hypothesis H3.

Panel H4-1 presents the fixed effects model estimations with the inclusion of Monday, Tuesday, Wednesday and Thursday dummy variables and therefore enables to examine the Monday-Friday return relationship directly. The direct comparison between Monday and Friday returns constitutes the traditional definition of the weekend effect, and in the light of prior findings in Panel H1-H3, I expect a weekend effect for index return to be strongest and most pronounced when investigating it through this lens. While Panel H4-1 sets Friday as the reference category, Panel H4-2 sets Monday as the reference category thus shows interesting correlations between returns on Friday and other weekday and is presented for comparison reasons. The coefficient of the Monday dummy in Panel H4-1 is negative and statistically significant at the 5% level (p-value 0.0404), which translates into Monday returns being significantly lower compared to Friday returns, ceteris paribus. To put it in numbers, Monday returns are approximately 0.069% lower compared to Friday returns, ceteris paribus. The coefficients of the control variables USDEURchange and hlmean are statistically significant at the 5% level and 0.1% level, respectively, and feature a negative correlation with daily logarithmic index returns. The coefficient of yesterday’s logarithmic return, which accounts for first-order autocorrelation, is positive and not statistically significant at the 5% level (p-value 0.1040). Consequently, in the light of findings from Panel H4-1, I reject the null hypothesis at the 5% and accept alternative hypothesis H4 as a find statistical evidence that Monday returns are significantly smaller compared to Friday returns, ceteris paribus. Even though I am able to determine a statistically significant weekend effect when comparing Monday and Friday returns directly, the magnitude of this effect is rather small. The economic significance of this effect is discussed in chapter 4. Interestingly, the coefficients of the Monday to Thursday dummies in Panel H4-1 monotonically increase by absolute numbers, which indicate that daily returns are lowest on Monday compared to Friday and monotonically increase over the week with highest returns on Friday.

Since I now established statistical evidence for a weekend as tested in alternative H4, I will continue be examining whether behavioural explanations, in particular indirect proxies of investor sentiment, are able to explain and serve as a valid mediator variables for the detected traditional weekend effect. The analysis of behavioural explanations for the weekend effect is presented in detail in the upcoming chapter.

3.3.2. Analysis of behavioural explanations for the weekend effect

In this chapter, I will examine whether indirect proxies of investor sentiment being daily returns of volatility indices, daily gold future returns as well as average daily German government bond returns serve as valid mediator variables for the weekend effect. As previously mentioned, the traditional definition of the weekend effect implies the direct comparison between Friday and Monday returns. Additionally, as the weekend effect analysis in chapter 3.3.1 reveals, the direct comparison between Friday and Monday returns as tested in hypothesis H4 (Panel H4-1) yields the strongest indication of a weekend-related effect on daily index returns, which is statistically significant at the 5% level and magnitude-wise also highest as compared to all other weekday-return comparisons examined in Panels H1-H3. Due to this, I will examine behavioural explanations for the weekend effect in this paper based on the fixed effects model specification from Panel H4-1 by conducting a popular three-step approach by Baron & Kenny (1986) that encompasses testing for statistical mediation.

In simple terms, a mediator or mediating variable is a variable Z, which conveys the effect of X on Y in a causal relationship structure that is X → Z → Y.

A mediation model, therefore, implies that the independent variable influences the mediator variable, which in turn influences the dependent variable; thus, the direct relationship between X and Y is either less significant in the case of a partial mediation and not significant (anymore) in the case of a full mediation of Z.

According to Baron & Kenny (1986), the following three requirements need to be met to verify a mediation effect as explained based on a simple regression model:

1. X is a significant predictor for Y (b_{yx} is statistically significant in the regression model $Y = b_0 + b_{yx}(X) + e$)
2. X is a significant predictor for the mediator variable Z (b_{zx} is statistically significant in the regression model $Z = b_0 + b_{zx}(X) + e$)

3. Z is a significant predictor for Y after controlling for X (b_{yz} is statistically significant in the regression model $Y = b_0 + b_{yx}(X) + b_{yz}(Z) + e$)
   3.1. In the case of a full mediation of Z, the effect of X on Y (b_{yx}) must not be significant anymore after controlling for Z
   3.2. In case of a partial mediation of Z, the effect of X on Y (b_{yx}) must be less significant and smaller in absolute value as compared to the coefficient of X in step 1 (b_{yx}) after controlling for Z.

In the context examining behavioural explanations for the weekend effect, the latter presented approach translates into testing whether indirect proxies of investor sentiment (Z) are able to clarify the nature of the relationship between the day of the week (X) and daily index returns (Y).

The first requirement to verify a mediation of investor sentiment on the weekend effect has already been met and established in the previous chapter where I statistically prove that Monday returns are smaller compared to Friday returns, ceteris paribus, with this finding being statistically significant at the 5% level (alternative hypothesis H4). However, since the magnitude of this effect is very small and translates into a decrease of daily index returns of only approximately -0.069% if the weekday is a Monday compared to being a Friday, ceteris paribus, it could be problematic to verify a mediation for such small numbers.

3.3.2.1. Second step of the mediation testing approach

The second requirement according to Baron & Kenny (1986) involves running regressions of the mediator variable under study on the independent variables of the model from step 1. The results of the respective fixed effects regressions regarding step 2 of the mediation testing approach are displayed at the end of chapter 3.3 in table 3.

The Monday dummy coefficient displayed in Panel H1b-1M and H1b-2M, which test whether daily returns of the volatility indices VSTOXX (H1b-1M) and VDAX (H1b-2M) are statistically different on Monday compared to Friday, is positive and statistically significant at the 0.1% level. A positive and statistically significant Monday coefficient in both Panel H1b-1M and H1b-2M reveal that Mondays are associated with increases in the expected volatility of the EURO STOXX 50 and DAX index, respectively, compared to Fridays thus market participants could be described as being more nervous on Mondays versus Fridays. Latter finding fulfils the second requirement in the context of mediation testing as by Baron & Kenny (1986) since a mediator variable is only able to covey an observed relationship if the mediator is also related to the independent variable of that observed relationship; otherwise, there would be nothing to mediate. Numerically speaking, Mondays feature an increase in daily VSTOXX (VDAX) volatility index returns of approximately 2.32% (2.17%) compared to Fridays, ceteris paribus. Similar as in Panel H4-1, the coefficients of the Monday to Thursday dummies feature a monotonically decreasing series in terms of numbers, which indicates that implicit volatility returns and therefore investor fear is highest on Monday and monotonically decreases in the course of a week with lowest market tension observed on Fridays.

In Panel H2b-1M and H2b-2M, I test whether the second step of the mediation testing approach is met regarding average daily German government bond returns with durations of 10 and 30 years, respectively, as the mediator variables under study. The Monday dummy coefficient turns out to be very similar in both fixed effects regressions with average daily returns of German government bond with a duration of 10 years (H2b-1M) and 30 years (H2b-2M), respectively, as dependent variables. In both cases, the coefficient features a positive sign and is statistically significant at the 0.1%, which reveals a positive relation between Monday and average daily German government bond returns compared to Friday; however, the magnitude of this effect is considerably smaller as the previously detected relation between volatility index returns and the day of the week. Nevertheless, this finding indicates that on Mondays, investors seem to have a tendency to buy (or a reluctance to sell) assets that are considered as safe and of high quality compared to Fridays, which is reflected in the increase of daily German government bond returns on Monday versus Friday. Numerically speaking, both German government bond categories with 10-year and 30-year duration exhibit an approx. 0.016% higher average return on Mondays compared to Fridays, ceteris paribus, which might translate into investors being more cautious and less risk-seeking on Monday compared to Friday.

The alternative hypothesis H3b, which involves the examination of daily gold future returns denoted in USD and EUR as indirect proxies of investor sentiment for the weekend effect, is tested in regards to the second step of the mediation analysis in Panel H3b-1M and H3b-2M, respectively. Despite the fact that daily gold future returns and average daily German government bond returns have the same spirit from a behavioural perspective, the sign of the Monday coefficient is negative in Panel H3b-1M and H3b-2M and thus stands in contrast to the coefficients displayed in Panel H2b-1M and H2b-2M. The finding of quite similar lower gold future returns for both notations in USD and EUR on Mondays compared to Fridays is statistically significant at the 0.1% level and indicates that investors are less willing to buy (or more willing to sell) gold on Monday compared to Friday. This finding contradicts my initial assumption of higher gold returns on Mondays compared to Fridays as regarded from a behavioural perspective. Since gold prices are determined by an interplay of various forces such as the oil price, prices of other commodities, interest rates, speculations as well as political events, it is likely that daily gold returns are not able to reflect investor emotions such as a fear of inflation or caution and therefore are possibly inadequate in reflecting sentiment among investors.

3.3.2.2. Third step of the mediation testing approach – final mediation models

After the second requirement in testing mediation according to the Baron & Kenny (1986) approach is now fulfilled for the hypothetical mediator variables under study, I construct mediated models in line with step 3 of the mediation testing approach to finally assess whether the 'traditional' weekend effect as tested in H4 is (at least partly) conveyed by the respective mediator variables.

The regression estimates of the final mediated models that feature the same model specification as tested in H4 except of having an additional mediator variable included as an independent variable, are outlined in table 4 at the end of chapter 3.3. Panels H1b-1 and H1b-2 display the regression outputs of the final mediated models in regards to the examined alternative hypothesis H1b, which claims that daily volatility index returns are at least to some extent able to explain the weekend effect from a behavioural perspective. The mediator variables vstoxxreturn in Panel H1b-1 and vdaxreturn in Panel H1b-2 take on a negative sign in both cases and are statistically significant at the 0.1% level and 1% level, respectively. Besides the assumed ability of (implicit) volatility indices such as VSTOXX and VDAX to reflect investor sentiment to some extent, their performance is commonly negatively related to their underlying stock index, which is reflected in the highly negative coefficient of both daily volatility return variables in the presented regression outputs. Intuitively, such finding seems plausible since a rise of fear among market participants (increasing volatility index returns) tends to result in a decreased demand for risky assets and thus a decline in stock prices. To test whether the weekend effect mediated by indirect sentiment measures such as daily volatility index returns, we also have to take a close look at the coefficient of the Monday dummy in the displayed regression estimates. As mentioned before, the coefficient the Monday dummy variable must not be statistically significant anymore and/or be smaller in absolute numbers in the final mediation models in the case of a full mediation and partial mediation, respectively. In the case of the mediated models presented in Panel H1b-1 and H1b-2, I find that in both cases the Monday dummy coefficient surprisingly changes its direction and now takes on a positive sign while still being statistically significant at the 5% level.

This outcome indicates multicollinearity, in particular, collinearity between the respective mediator variable vstoxxreturn or vdaxreturn and the Monday dummy variable. Table 5 at the end of chapter 3.3 displays a correlation matrix of all the variables applied in the mediation models. Correlation statistics reveal that daily returns of both volatility indices exhibit a similar, relatively high, positive correlation with Mondays, numerically speaking a correlation of approximately 0.13. Consequently, the sign reversal of the Monday dummy coefficient in the mediated models shown in Panel H1b-1 and H1b-2 can be explained by the fact that Mondays and volatility index returns both feature a negative correlation with the dependent variable, logarithmic stock returns, while these two independent variables itself feature a positive correlation. Furthermore, the negative effect of volatility index returns on logarithmic stock returns is much stronger as compared to the detected weekend effect, which also contributes to the sign reversal of the Monday coefficient. However, since the Monday has not lost its statistical significance in the mediated models shown in Panel H1b-1 and H1b-2, I conclude that volatility index returns are not able to mediate the weekend effect and therefore do not serve as a behavioural explanation for this market anomaly. Consequently, I cannot reject the null hypothesis in the context of testing mediation for the weekend effect that investor sentiment as measured indirectly by daily volatility index returns is not able to explain the weekend effect.

In Panel H2b-1 and H2b-2, I present the estimation outcomes of the mediated models in regards to daily German government bond returns as included mediator variables. While the coefficients of the bund10return and bund30return variables both are negative and statistically significant at the 5% level in the final mediation models, the magnitude of the negative effect of average daily bond returns with a duration of 10 years is considerably greater compared to the estimated effect of average daily bond returns with a duration of 30 years. Numerically speaking, an increase of 1% in average daily German bond returns with a duration of 10 and 30 years is associated with a decrease in daily stock returns of approximately -0.192% and -0.124%, respectively, ceteris paribus. As compared to the Monday dummy coefficient of -0.00069288 and a p-value of 0.0404 in the weekend analysis regression from Panel H4-1, the Monday dummy coefficient in the mediated model shown in Panel H2b-2 (30-year bond returns) slightly decreased in size and partially lost its statistical significance, however, the association remains significant at the 5% level. I thus conclude that average daily German government bond returns with a duration of 30 years are not able to mediate the weekend effect and the null-hypothesis in the context of analysing behavioural explanations for the weekend cannot be rejected for this specific sentiment measure. The mediation models that include average daily returns of German government bonds with a duration of 10 years as shown in Panel H2b-2 draw a different picture as portrayed in Panel H2b-1. After including the mediator variable bund10return in the fixed effects model, the Monday dummy coefficient turns out to be not statistically significant anymore at the 5% level (p-value of 0.0539). This outcome indicates that lower returns on Mondays compared to Fridays can to some extent be explained by investor sentiment, namely by an increased demand of assets that are considered as safe and of high quality due to increased concerns, nervousness and possibly fear among investors on Mondays compared to Fridays.

Since the Baron & Kenny (1986) three-step approach indicates valid partial mediation, I conducted an additional mediation analysis based on structural equation modelling (SEM) which results are presented in table 6. SEM enables me to distinguish between direct and indirect effects in the context of mediation testing. The direct and indirect effects on daily logarithmic returns are estimated based on a reduced model that only comprises daily logarithmic returns as the dependent variable, Monday to Thursday dummy variables and average daily returns of German government bonds with a duration of 10-years. The direct effect section in table 6 refers to the direct effect of Monday on logarithmic stock index returns in consideration of a mediation by average daily 10-y. German government bond returns. The indirect effect section refers to the effect of Monday on logarithmic stock index returns that passes through the mediator variable namely average daily 10-y. German government bond returns. The total effect section in turn displays the total effect of Monday on logarithmic stock index returns under the assumption that no mediation variable is included in the model. Thus, the sum of direct and indirect effect yields the total effect.

The proportion of the total effect that is mediated in this reduced model (ratio of indirect to total effect) is approx. 4.22% and therefore rather low.

The ratio of the indirect effect to the direct effect is approx. 4.4% and thus as well quite small. All effect paths in this SEM approach are statistically significant at least at the 1% level as the respective z-values indicate; I therefore conclude that the weekend effect to small extent can be explained by investor sentiment as indirectly measured by average German government bond returns with a duration of 10-years. Thus, I find mixed support for the alternative hypothesis H2b since I show that 30-y. German government bond returns are not able serve as a valid mediator for the weekend effect while average daily returns of German government bonds with a duration of 10 years are at least able to convey a small fraction of the negative effect of Mondays on stock returns compared to Fridays.

Finally, in the context of testing alternative hypothesis H3b, I include daily gold future returns denoted in USD and EUR as intervening variables in the final mediation models, which outputs are shown in Panel H3b-1 and H3b-2, respectively. Since the coefficients of both mediator variables goldusdreturn and goldeurreturn turn out to be statistically insignificant at the 5% level while the Monday coefficients remain statistically significant at the 5% level in both mediation models, I conclude that daily gold future returns in both notations do not serve as valid mediator variables for the weekend effect as tested in H1b. Consequently, I cannot reject H0b in the context of examining behavioural explanations for the weekend effect, which states that indirect proxies of investor sentiment are not able to explain at least some parts of the weekend effect.

In summary, it can be stated that indirect proxies of investor sentiment might indeed give some indication about sentiment among investors during a week, which is reflected in the statistically significant Monday coefficients in step two of the mediation testing approach (table 3). However, when it comes to explaining the traditional weekend effect – the association between returns on Monday compared to Friday – I find that these indirect measures of investor sentiment under study are barely able to explain this market anomaly. Some statistical evidence for a valid mediation of the weekend effect is ascertained for average daily returns of German bonds with a duration of 10 years; however, the magnitude of the mediation effect of this indirect investor sentiment measure is rather small.

Thus, I am not able to reject the null hypothesis in regards to the examination of alternative hypothesis H1b and H3b and found mixed support for alternative H2b with average daily 10-y. German government bond returns being a statistically significant mediator variable for the weekend effect while average daily 30-y. German government bond returns are not.

Economically speaking, the magnitude of the detected mediation effect of average daily 10-y. German government bond returns on the weekend effect of under 5%

according to estimates of the SEM is quite small and thus can be considered as rather insignificant. This especially is true in the light of the magnitude-wise rather small weekend effect detected in the data, which indicates a daily return difference of only approx. -0.069% between Monday and Friday as shown in Panel H4-1.
In the following chapter, I examine the robustness of the weekend effect as tested in the alternative hypotheses H1-H4 by running fixed effects regressions based on computed estimates of a GARCH(1,1) model.

3.3.3 Robustness checks

In this chapter, I check the robustness of previous findings from the weekend effect analysis outlined in chapter 3.3.1 by first fitting a GARCH(1,1) model to the data under study (individually for each stock index) and consequently using the respective GARCH(1,1) model estimates within appropriate statistical models that test for a weekend-related effect on stock index returns. From an econometric perspective, this approach involves running fixed effects regressions of the conditional mean daily return estimates from a GARCH(1,1) model (GARCH_Residual) on respective weekday dummy variables while controlling for the USD/EUR exchange rate and the conditional variance of daily logarithmic returns (GARCHcondVar). The conditional variance of daily returns also originates from the GARCH(1,1) model and reflects the variance of log-returns for each stock index separately conditional on its past performance. A comparison between the computed 'GARCHcondVar' variable and the previously used alternative variance measure 'hlmean' is presented in Figure 4 below, which reveals that the GARCH(1,1) model did a good job in predicting the conditional variance of daily log-return for each index. Even though the GARCH(1,1) model relies on less information about daily price fluctuations or deviations since it is only based on the logarithmic return series of the indices and thus solely on the indices' closing prices while the alternative variance measure hlmean draw on additional price information including daily high and low prices, both variance measures turn out to have a surprisingly similar shape. The fixed effects regressions discussed in this section have the same objective and a similar construction as the regressions from the weekend analysis presented in chapter 3.3.1 and are displayed at the end of this chapter due to reasons of clarity and comprehensibility. Panel H1-1G and H1-2G test the alternative hypothesis H1 in the context of its statistical robustness. The coefficient for the Monday dummy versus Tuesday-Friday as displayed in Panel H1-1G is negative albeit not statistically significant at the 5% level, which is compliant with my findings from Panel

H1-1 of the weekend effect analysis. Panel H1-2G confirms that Friday returns are higher compared to Monday-Thursday returns with this effect being statistically significant at the 5% level, which likewise is consistent with my findings from the weekend effect analysis. Thus, I cannot reject H0 based on the outcomes of these model specifications, which is congruent with my conclusion from the weekend effect analysis regarding alternative hypothesis H1.

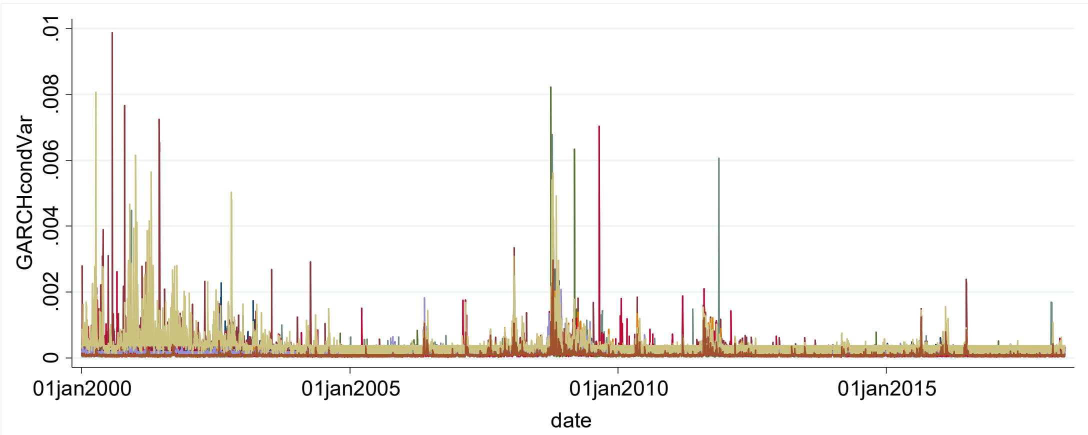
The second alternative hypothesis H2 based on the GARCH(1,1) model estimates is tested in Panel H2G, which shows the outcomes of the model specification that examines Monday and Friday returns versus Tuesday-Thursday returns. In accordance with my findings from the previous weekend effect analysis, I find that Friday returns are higher, and Monday returns are lower compared to Tuesday-Thursday returns, though only the Friday dummy features a positive and statistically significant (at the 5% level) coefficient while the Monday dummy coefficient is not statistically significant at the 5% level. Consequently, I again cannot reject H0 for this specific model specification in the context of robustness checks.

Estimates of the fixed effects regression that examines the third alternative hypothesis H3 in the context of its statistical robustness are presented in Panel H3G. The output of this specific model specification, which sets Wednesday as the reference category, reveals that both Friday returns are higher and Monday returns are lower compared to Wednesday returns; however, only the positive Friday dummy coefficient is statistically significant at the 1% level while the negative Monday dummy coefficient is not statistically significant at the 5% level. Thus, I cannot reject H0 for this model specification within the frame of robustness checks.

Panel H4-1G and H4-2G, which examine the traditional definition of the weekend effect, i.e. the difference between Monday and Friday returns directly, confirm prior findings drawn from the weekend effect analysis in chapter 3.3.1 and reveal that the difference in returns between Monday and Friday is statistically significant at the 5%. According to the shown fixed effects regression outputs, Monday returns are significantly lower compared to Friday returns while controlling for daily USD/EUR exchange rate changes and the conditional variance of daily index returns. Therefore, it seems that the Monday-Friday return relationship also holds in this model specification with GARCH(1,1) estimates that account for first-order autocorrelation and heteroscedasticity; thus, the traditional weekend effect seems to be robust albeit again is rather small in size.

In regards to this model specification, I can reject the null hypothesis at the 5% significance level that returns are equal during a week in favour of alternative hypothesis H4. Therefore, statistical evidence of a traditional weekend effect among nine European stock indices under study has been established, which is reflected in significantly higher index returns on Fridays compared to Mondays. While the true underlying reasons for this market anomaly remain unclear, behavioural explanations are already able to explain a large part of the weekend effect as shown by Birru (2017) and Bakar et al. (2014) and thus constitute a reference point for future academic research that is worth to be examined in depth.

Figure 5. Comparison between the conditional variance derived from a GARCH (1,1) model (GARCHcondVar) and the alternative variance measure 'hlmean'
This figure shows a comparison between the conditional variance of daily logarithmic index returns derived from a GARCH (1,1) model (upper graph) and the alternative variance measure hlmean (lower graph) used in previous fixed effects regressions of the baseline weekend effect analysis.



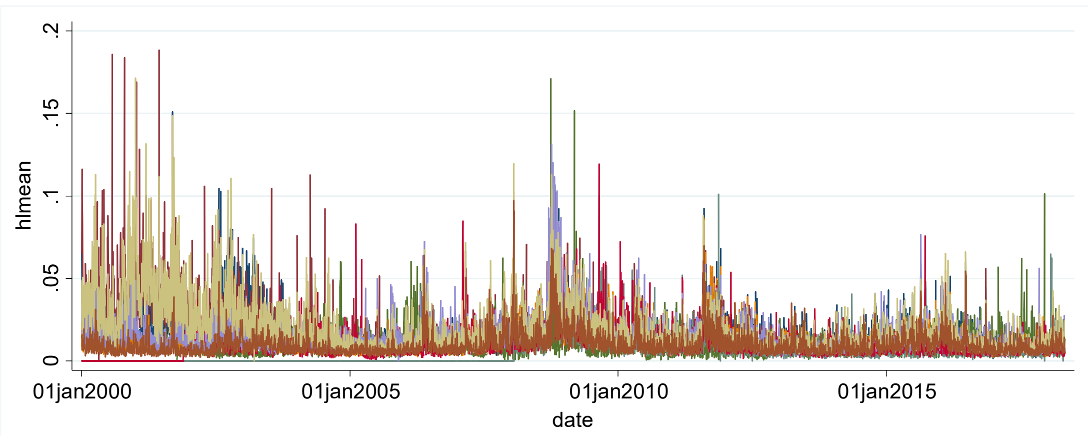


Table 2. Analysis of the weekend effect

The following table shows coefficients obtained from fixed effects panel regressions with standard errors adjusted for clusters (index). A full overview of the results is presented in the Appendix.

logreturn	Panel H1-1	Panel H1-2	Panel H2	Panel H3	Panel H4-1	Panel H4-2
mon	**-0.00042413**	-	**-0.00033567**	**-0.0002236**	**-0.00069288***	-
fri	-	**0.0004395***	**0.00035714**	**0.00046928***	**-**	**0.00069288***
USDEURchange	-0.08567791*	-0.08660855*	-0.08590508*	-0.08556104*	-0.08556104*	-0.08556104*
hlmean	-0.18039522***	-0.18013375***	-0.18021516***	-0.18043592***	-0.18043592***	-0.18043592***
logreturnyesterday	0.03549466	0.0352387	0.03537698	0.0353131	0.0353131	0.0353131
tue	-	-	-	-0.00012293	-0.00059221*	0.00010067
wed	-	-	-	-	-0.00046928*	0.0002236
thu	-	-	-	0.00046444*	-0.000004837	0.00068804*
_cons	0.00271645***	0.00254244***	0.00262578***	0.00251653***	0.00298581***	0.00229293***
N	41590	41590	41590	41590	41590	41590
r2	0.02703195	0.02704483	0.02713514	0.02734368	0.02734368	0.02734368
r2_a	0.02693836	0.02695125	0.02701817	0.02717994	0.02717994	0.02717994

legend: * p<0.05; ** p<0.01; *** p<0.001

Table 3. Analysis of behavioural explanations for the weekend effect as tested in alternative hypothesis H4 – step 2 of the mediation analysis
The following table shows coefficients obtained from fixed effects panel regressions with standard errors adjusted for clusters (index). A full overview of the results is presented in the Appendix.

Dependent variable:	Panel H1b-1M **vstoxxreturn**	Panel H1b-2M **vdaxreturn**	Panel H2b-1M **bund10return**	Panel H2b-2M **bund30return**	Panel H3b-1M **goldusdreturn**	Panel H3b-2M **goldeurreturn**
mon	**0.023279*** **	**0.02167798*** **	**0.0001675*** **	**0.0001679*** **	**-0.00149307*** **	**-0.00164003*** **
tue	0.0056226***	0.0053775***	-0.00006357***	-0.0001116***	-0.00152342***	-0.00158583***
wed	0.00478943***	0.00592816***	-0.00023622***	-0.00038016***	-0.00131814***	-0.00138912***
thu	0.00094054**	0.00271013***	0.00054278***	0.00072101***	-0.00181241***	-0.00187207***
USDEURchange	0.10073562***	-0.00223509	-0.02399412***	-0.008793***	-0.64377048***	0.33987288***
hlmean	0.72046562***	0.55825579***	-0.00056971	-0.00264688	0.01060425**	0.00814084*
logreturnyesterday	0.13498375***	0.04477528**	0.00016838	0.00479301*	0.01340282**	0.01004618*
_cons	-0.01480578***	-0.01322566***	-0.0000184	0.00006947*	0.00147522***	0.00154056***
N	41590	41590	41590	41590	41590	41590
r2	0.03527632	0.03147847	0.00695932	0.00441463	0.13223069	0.04398838
r2_a	0.03511392	0.03131543	0.00679215	0.00424703	0.13208461	0.04382745

legend: * p<0.05; ** p<0.01; *** p<0.001

Table 4. Analysis of behavioural explanations for the weekend effect as tested in alternative hypothesis H4 – step 3 of the mediation analysis

The following table shows coefficients obtained from fixed effects panel regressions with standard errors adjusted for clusters (index). A full overview of the results is presented in the Appendix.

logreturn	Panel H1b-1	Panel H1b-2	Panel H2b-1	Panel H2b-2	Panel H3b-1	Panel H3b-2
mon	**0.00172455***	**0.00180851***	**-0.00065721**	**-0.00067061***	**-0.00068777***	**-0.00068141***
tue	-0.000008328	0.00002829	-0.00060575*	-0.00060701*	-0.00058699*	-0.00058112*
wed	0.00002809	0.00021477	-0.00051958*	-0.00051969*	-0.00046476*	-0.00045956*
thu	0.00009283	0.00030788	0.00011075	0.00009079	0.000001371	0.000008256
USDEURchange	-0.07510007*	-0.08581895*	-0.09067056*	-0.0867272*	-0.0833559**	-0.08793817*
hlmean	-0.10561858***	-0.11601951***	-0.18055724***	-0.18078696***	-0.18047224***	-0.18049286***
logreturnyesterday	0.0493306*	0.04047966	0.03534896	0.03594877	0.03526719	0.03524284
vstoxxreturn	**-0.10384581*****	-	-	-	-	-
vdaxreturn	-	**-0.11538869****	-	-	-	-
bund10return	-	-	**-0.21294895***	-	-	-
bund30return	-	-	-	**-0.13262369***	-	-
goldusdreturn	-	-	-	-	**0.00342535**	-
goldeurreturn	-	-	-	-	-	**0.00699416**
_cons	0.00144829**	0.00145971**	0.00298189***	0.00299502***	0.00298075***	0.00297503***
N	41590	41590	41590	41590	41590	41590
r2	0.24455966	0.2381704	0.03063524	0.03044485	0.02735076	0.02737316
r2_a	0.24441431	0.23802383	0.03044874	0.03025831	0.02716363	0.02718603

legend: * p<0.05; ** p<0.01; *** p<0.001

Table 5. Correlation matrix

The following table displays correlations between selected variables used in respective fixed effects regression models in this paper

	logreturn	mon	tue	wed	thu	fri	vstoxx-return	vdax-return	bund10-return	bund30-return	goldusd-return	goldeur-return
logreturn	1											
mon	-0.0126	1										
tue	-0.0087	-0.249	1									
wed	-0.0049	-0.249	-0.254	1								
thu	0.0109	-0.247	-0.252	-0.252	1							
fri	0.0154	-0.246	-0.251	-0.251	-0.249	1						
vstoxxreturn	-0.479	**0.1307**	-0.01	-0.017	-0.046	-0.057	1					
vdaxreturn	-0.4712	**0.1308**	-0.016	-0.011	-0.038	-0.066	0.863	1				
bund10return	-0.0545	0.0103	-0.019	-0.044	0.0638	-0.011	0.071	0.088	1			
bund30return	-0.0531	0.0077	-0.017	-0.041	0.0563	-0.007	0.075	0.099	0.901	1		
goldusdreturn	0.0179	-0.023	-0.009	-0.005	-0.017	0.0534	0.01	0.013	0.0704	0.07	1	
goldeurreturn	-0.0031	-0.009	-0.016	-0.004	-0.031	0.0603	0.014	0.012	0.0491	0.0695	0.8332	1

Table 6. Mediation analysis of 'bund10return' based on structural equation modelling (SEM)

The following tables present the additional mediation analysis of the intervening variable 'bund10return' on the weekend effect based on a SEM, which yields direct effects, indirect effects and total effects. The results contribute towards comprehending the respective effect paths in this reduced statistical model.

Direct effects	Coef.	OIM Std. Err.	z	P>|z|	[95% Conf. Interval]	
Structural						
bund10return ←						
mon	0.0001577	0.0000572	2.76	0.006	0.0000457	0.0002698
tue	-0.0000594	0.0000568	-1.05	0.295	-0.0001707	0.0000518
wed	-0.0002365	0.0000567	-4.17	0	-0.0003476	-0.0001253
thu	0.0005498	0.0000569	9.66	0	0.0004382	0.0006614
logreturn ←						
bund10return	-0.2049033	0.0181546	-11.29	0	-0.2404856	-0.169321
mon	**-0.0007331**	**0.0002117**	**-3.46**	**0.001**	**-0.0011481**	**-0.0003181**
tue	-0.0006679	0.0002102	-3.18	0.001	-0.0010798	-0.000256
wed	-0.0006012	0.0002101	-2.86	0.004	-0.0010129	-0.0001895
thu	-0.00001	0.000211	-0.05	0.962	-0.0004236	0.0004036

(continued)

Indirect effects	Coef.	OIM Std. Err.	z	P>|z|	[95% Conf. Interval]	
Structural						
bund10return <-						
mon	0	(no path)				
tue	0	(no path)				
wed	0	(no path)				
thu	0	(no path)				
logreturn <-						
bund10return	0	(no path)				
mon	**-0.0000323**	**0.0000121**	**-2.68**	**0.007**	**-0.000056**	**-0.00000868**
tue	0.0000122	0.0000117	1.04	0.297	-0.0000107	0.0000351
wed	0.0000485	0.0000124	3.91	0	0.0000242	0.0000727
thu	-0.0001127	0.0000154	-7.34	0	-0.0001428	-0.0000826

(continued)

Total effects	Coef.	OIM Std. Err.	z	P>|z|	[95% Conf. Interval]	
Structural						
bund10return <-						
mon	0.0001577	0.0000572	2.76	0.006	0.0000457	0.0002698
tue	-0.0000594	0.0000568	-1.05	0.295	-0.0001707	0.0000518
wed	-0.0002365	0.0000567	-4.17	0	-0.0003476	-0.0001253
thu	0.0005498	0.0000569	9.66	0	0.0004382	0.0006614
logreturn <-						
bund10return	-0.2049033	0.0181546	-11.29	0	-0.2404856	-0.169321
mon	**-0.0007654**	**0.000212**	**-3.61**	**0**	**-0.001181**	**-0.0003498**
tue	-0.0006557	0.0002105	-3.12	0.002	-0.0010682	-0.0002432
wed	-0.0005528	0.0002103	-2.63	0.009	-0.000965	-0.0001406
thu	-0.0001227	0.0002111	-0.58	0.561	-0.0005365	0.0002912

Table 7. Robustness checks of the weekend effect based on GARCH(1,1) model estimates

The following table shows coefficients obtained from fixed effects panel regressions with standard errors adjusted for clusters (index). A full overview of the results is presented in the Appendix.

GARCH_Residual	Panel H1-1G	Panel H1-2G	Panel H2G	Panel H3G	Panel H4-1G	Panel H4-2G
mon	**-0.00038223**	**-**	**-0.00026847**	**-0.00017579**	**-0.00072828***	**-**
fri	**-**	**0.00052555***	**0.00045976***	**0.00055249****	**-**	**0.00072828***
USDEURchange	-0.09164675*	-0.09249553*	-0.09193258*	-0.0916456*	-0.0916456*	-0.0916456*
GARCHcondVar	-0.06230932	-0.06030016	-0.06418814	-0.05693451	-0.05693451	-0.05693451
tue	-	-	-	-0.00011937	-0.00067186*	0.00005642
wed	-	-	-	-	-0.00055249**	0.00017579
thu	-	-	-	0.00040184*	-0.00015064	0.00057763*
_cons	-0.00033184**	-0.00051168***	-0.00044513***	-0.00053929**	0.0000132	-0.00071507**
N	41590	41590	41590	41590	41590	41590
r2	0.00198127	0.00209458	0.00215236	0.0023144	0.0023144	0.0023144
r2_a	0.00190927	0.00202259	0.00205638	0.00217045	0.00217045	0.00217045

legend: * p<0.05; ** p<0.01; *** p<0.001

4. Methodological constraints & implications of findings

In this chapter, I address selected constraints in regards to my applied empirical approach in the course of examining the existence of the weekend effect as well as of testing behavioural explanations for this market anomaly. Subsequently, I will outline important implications of my findings.

Although I provide statistical evidence of the traditional weekend effect in the data under study as I detect significantly lower stock index returns on Mondays compared to Fridays, this market anomaly remains a mystery that leaves behind many yet unanswered questions.

To get a better understanding of the weekend effect, one first has to make up his mind about the data under study. In this paper, I examined the weekend effect on the basis of daily stock index returns of nine European total-return indices, which might constitute the first constraint regarding my empirical approach. It is very likely that the weekend effect differs in size across the nine stock indices under study and that this market anomaly is present in one examined index while another index under study displays no such weekend effect or even features a reverse weekend effect (i.e. higher returns on Monday compared to Friday). Regarding the presented statistical analyses in this paper that are based on the aggregated daily returns of all nine stock indices under study, latter assumptions can cause possible index-individual opposing weekend effects to cancel each other out, which may explain the magnitude-wise rather small 'overreaching' weekend effect. As compared to previous findings on the weekend effect by Cross (1973), who documents that the mean percentage difference between Monday and Friday S&P stock index prices in a sample period from 1953 to 1970 amounts to approximately 0.3%, the detected difference in returns between Monday and Friday of only 0.069% in my data under study can be regarded as small and less economically significant.

Differences in a possible weekend effect between indices can have several reasons: it might be due to cultural differences between countries or regarding Germany with four indices under study, due to a different constitution of these indices and thus different characteristics of the comprising stocks. A further breakdown into countries and/or sectors would allow to dig deeper into the mechanisms of this effect and might reveal promising results. In addition, a weekend effect that is examined based on daily stock returns directly would also allow to discriminate between different stock characteristics and thus might indicate that some stocks with specific features are more likely to be affected by such weekday-related return effects while others might be resistant to this market anomaly.

Incorporating international stock indices or international single stocks in respective analyses yields a more extensive data set which also might provide a clearer picture of the weekend effect, however, a large sample size also favours the finding of anomalies and thus bias outcomes as shown by Connolly (1991 and 1989), which they refer to as the 'Lindley Paradox'.

Nevertheless, empirical research based on a large sample size of international stock indices, including countries like the United Arab Emirates (UAE) that feature a different weekend compared to our Western world weekend definition, might provide further insights into the weekend effect.

Furthermore, intraday analyses would also provide a better understanding of the weekend effect since it allows the researcher to distinguish if a negative Monday return is due to the non-trading period on the weekend or due to active trading on Monday. Since the examined dataset in this paper comprised only daily and no intraday index price quotes, I was not able to provide analyses that can distinguish whether the negative Monday return accrues in the non-trading or in the trading period.

Including additional information about the transaction type that leads to weekend effect within appropriate statistical models might by promising way to understand this market anomaly better since one would be able to distinguish if either a decreased (increased) demand or an increased (decreased) supply of stocks leads to the often observed Monday decline (Friday increase) in stock prices.

In the context of examining behavioural explanations for the weekend effect, I find mixed statistical evidence that investor sentiment is able to explain the weekend effect to a very small extent. Measuring investor sentiment is a challenging undertaking, especially when it comes to measuring mood among investors on a daily basis. Many common proxies of investor sentiment are measured in periods that range longer than one day and therefore are inappropriate in examining the weekend effect. Limited statistical evidence in the presented analyses of behavioural explanations for the weekend effect might also be due to the use of indirect proxies of investor sentiment such as volatility index returns, average German government bond returns or gold future returns instead of direct proxies of investor sentiment.

Such direct proxies of investor sentiment are often based on huge databases of social networks like Facebook or Twitter or sometimes rely on Google search inputs. These direct measures might reflect changes in sentiment among investors to a stronger degree as compared to indirect proxies of investor sentiment. Indirect proxies of investor sentiment represent a mixture or conglomerate of different forces, which makes it difficult to attribute a specific outcome solely to the sentiment of investors. In summary, investor sentiment is quite hard to measure in isolation, however, the steadily increasing amount of information on the internet, in particular in social networks along with the availability of sufficient computing power to gather and process this data, enables researchers to construct measures that reflect investor sentiment more precisely.

Despite the fact that I detected a statistically significant weekend effect in my data and found mixed statistical evidence that investor sentiment as measured by average daily 10-y. German government bond returns drives this effect to a small extent, the magnitude of these findings are rather small. The outputs of the conducted fixed effects regressions in this paper reveal that the estimated difference in returns between Monday and Friday is less than 0.1% and therefore can be considered as little economically significant. The same holds true for the detected mediation effect of daily 10-y. German government bond returns on the weekend effect: limited economic significance is reflected in the finding that this indirect investor sentiment measure is only able to explain less than 5% of the total weekend effect according to conducted SEM analyses. Due to this, trading strategies based on weekly return patterns such as the weekend effect are likely to turn out unprofitable since trading costs would offset a hypothetical (small) gain owing to the exploitation of this anomaly.

5. Conclusion

This paper's main objective for one is to test whether daily returns of nine European stock market indices, in particular returns on days surrounding a weekend, feature a weekly pattern thus are on average significantly different during a week and for another to examine whether behavioural explanations, in particular investor sentiment, is able to explain a potential weekend effect in my data.

The conducted statistical analyses reveal that returns on Monday are significantly lower compared to Friday returns, which is in line with previous literature that likewise examined the traditional definition of the weekend effect i.e. the direct relationship between Monday and Friday stock returns (see f.e. Cross, 1973). However, the magnitude of the detected weekend effect is rather small and thus less economically significant. Furthermore, I am able to provide evidence that investor sentiment as indirectly measured by average daily returns of German government bond with a duration of 10 years is able to explain the weekend effect to a small extent.

Because the degree to which investor sentiment drives the weekend effect is rather low, the detected mediation of investor sentiment for this market anomaly can likewise be considered as less economically significant. Nevertheless, the findings in this paper give some indication about the weekly behaviour of aggregated selected European stock index returns and point out that the stock market is not as efficient as a traditional economist might assume. Generally speaking, people do not always behave rationally which of course also applies to participants of financial markets. It seems plausible that investors are somehow affected by the day of the week, especially in regards to their mood state, which might be better on Fridays and worse on Mondays due to the weekend, i.e. leisure time in between working weeks. This, in turn, might affect their trading behaviour and consequently be reflected in daily stock returns.

Direct measures of investor sentiment or mood based on enormous social media databases or Google search volumes possibly reflect the general well-being of individuals more precisely compared to indirect investor sentiment proxies. Therefore, the use of such direct sentiment proxies in empirical analyses might constitue a promising approach for future research to provide to provide further meaningful insights into the interrelation between human psychology and financial markets.

Furthermore, one might perform a comparison between countries that feature the traditional weekend from Sat-Sun and countries with different weekend definitions, f.e. Arabic countries from Fri-Sat, to see if the weekend effect is still present and if the mood or sentiment explanation still holds.

Further interesting research approaches regarding the weekend effect might comprise intraday analyses that enable researchers to determine the exact point in time at which specific return pattern accrue. Integrating more details about the transaction type, i.e. buying or selling of stocks, in analyses would likewise enable researchers to get a better understanding of this anomaly and would contribute towards solving this puzzling market inefficiency.

Appendix

Table 8. Full overview of the weekend effect analysis (in reference to table 2)

The table below shows the weekend effect analysis including coefficients, standard errors, t-values and p-values.

logreturn		Panel H1-1	Panel H1-2	Panel H2	Panel H3	Panel H4-1	Panel H4-2
	mon	**-0.0004241**		**-0.00033567**	**-0.0002236**	**-0.00069288**	
se		0.0001948		0.00017422	0.00020013	0.00028364	
t-value		-2.18		-1.93	-1.12	-2.44	
p-value		**0.0611**		**0.0902**	**0.2963**	**0.0404**	
	fri		**0.0004395**	**0.00035714**	**0.00046928**		**0.00069288**
se			0.00018399	0.0001617	0.0001682		0.00028364
t-value			2.39	2.21	2.79		2.44
p-value			**0.0439**	**0.0582**	**0.0236**		**0.0404**
	USDEURchange	-0.0856779	-0.08660855	-0.08590508	-0.08556104	-0.08556104	-0.08556104
se		0.0275264	0.02764257	0.02759603	0.02760359	0.02760359	0.02760359
t-value		-3.11	-3.13	-3.11	-3.1	-3.1	-3.1
p-value		0.0144	0.0139	0.0144	0.0147	0.0147	0.0147
	hlmean	-0.1803952	-0.18013375	-0.18021516	-0.18043592	-0.18043592	-0.18043592
se		0.0251574	0.02514154	0.02512169	0.02511159	0.02511159	0.02511159
t-value		-7.17	-7.16	-7.17	-7.19	-7.19	-7.19
p-value		0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
	logreturnyesterday	0.0354947	0.0352387	0.03537698	0.0353131	0.0353131	0.0353131
se		0.0192689	0.01925306	0.01927794	0.01925746	0.01925746	0.01925746
t-value		1.84	1.83	1.84	1.83	1.83	1.83
p-value		0.1027	0.1046	0.1038	0.104	0.104	0.104

(continued)

	tue				-0.00012293	-0.00059221	0.00010067
se					0.00012655	0.00020903	0.00013808
t-value					-0.97	-2.83	0.73
p-value					0.3598	0.022	0.4867
	wed					-0.00046928	0.0002236
se						0.0001682	0.00020013
t-value						-2.79	1.12
p-value						0.0236	0.2963
	thu				0.00046444	-0.000004837	0.00068804
se					0.00019078	0.00017584	0.00024007
t-value					2.43	-0.03	2.87
p-value					0.0409	0.9787	0.021
	_cons	0.0027165	0.00254244	0.00262578	0.00251653	0.00298581	0.00229293
		0.0003237	0.0003392	0.00032132	0.00032112	0.00035742	0.00041655
		8.39	7.5	8.17	7.84	8.35	5.5
		0	0.0001	0	0.0001	0	0.0006
	N	41590	41590	41590	41590	41590	41590
	r2	0.027032	0.02704483	0.02713514	0.02734368	0.02734368	0.02734368
	r2_a	0.0269384	0.02695125	0.02701817	0.02717994	0.02717994	0.02717994

Table 9. Full overview of conducted fixed effects regressions of step 2 of the mediation analysis (in reference to table 3)

The table below shows the second step of the mediation testing approach including coefficients, standard errors, t-values and p-values.

		Panel H1b-1M	Panel H1b-2M	Panel H2b-1M	Panel H2b-2M	Panel H3b-1M	Panel H3b-2M
	Dependent variable:	**vstoxxreturn**	**vdaxreturn**	**bund10return**	**bund30return**	**goldusdreturn**	**goldeurreturn**
	mon	**0.023279**	**0.02167798**	**0.0001675**	**0.0001679**	**-0.00149307**	**-0.00164003**
se		0.00026329	0.00021026	0.000003229	0.000003423	0.00003248	0.00003942
t-value		88.42	103.1	51.88	49.05	-45.97	-41.6
p-value		**0**	**0**	**0**	**0**	**0**	**0**
	tue	0.0056226	0.0053775	-0.00006357	-0.0001116	-0.00152342	-0.00158583
se		0.00015051	0.00015558	0.000003346	0.000005806	0.00002042	0.00001676
t-value		37.36	34.56	-19	-19.22	-74.59	-94.64
p-value		0	0	0	0	0	0
	wed	0.00478943	0.00592816	-0.00023622	-0.00038016	-0.00131814	-0.00138912
se		0.00018767	0.00013099	0.000003204	0.00000547	0.0000135	0.00001227
t-value		25.52	45.26	-73.73	-69.5	-97.65	-113.24
p-value		0	0	0	0	0	0
	thu	0.00094054	0.00271013	0.00054278	0.00072101	-0.00181241	-0.00187207
se		0.00019312	0.0001737	0.000005241	0.00000685	0.0000149	0.00001526
t-value		4.87	15.6	103.56	105.26	-121.63	-122.69
p-value		0.0012	0	0	0	0	0

(continued)

	USDEURchange	0.10073562	-0.00223509	-0.02399412	-0.008793	-0.64377048	0.33987288
se		0.00626116	0.00937037	0.00042299	0.000756	0.00174002	0.00171771
t-value		16.09	-0.24	-56.72	-11.63	-369.98	197.86
p-value		0	0.8175	0	0	0	0
	hlmean	0.72046562	0.55825579	-0.00056971	-0.00264688	0.01060425	0.00814084
se		0.10880804	0.09284505	0.0011335	0.00189464	0.00277184	0.00246597
t-value		6.62	6.01	-0.5	-1.4	3.83	3.3
p-value		0.0002	0.0003	0.6288	0.1999	0.005	0.0108
	logreturnyesterday	0.13498375	0.04477528	0.00016838	0.00479301	0.01340282	0.01004618
se		0.02482479	0.01327037	0.00130698	0.00176046	0.00348742	0.00304086
t-value		5.44	3.37	0.13	2.72	3.84	3.3
p-value		0.0006	0.0097	0.9007	0.0261	0.0049	0.0108
	_cons	-0.01480578	-0.01322566	-0.0000184	0.00006947	0.00147522	0.00154056
se		0.00139189	0.00118821	0.00001545	0.00002562	0.00004356	0.00003713
t-value		-10.64	-11.13	-1.19	2.71	33.87	41.49
p-value		0	0	0.2679	0.0266	0	0
	N	41590	41590	41590	41590	41590	41590
	r2	0.03527632	0.03147847	0.00695932	0.00441463	0.13223069	0.04398838
	r2_a	0.03511392	0.03131543	0.00679215	0.00424703	0.13208461	0.04382745

Table 10. Full overview of the final mediation models (step 3 of the mediation analysis; in reference to table 4)

The table below shows the third step of the mediation testing approach including coefficients, standard errors, t-values and p-values.

logreturn		Panel H1b-1	Panel H1b-2	Panel H2b-1	Panel H2b-2	Panel H3b-1	Panel H3b-2
	mon	**0.00172455**	**0.00180851**	**-0.00065721**	**-0.00067061**	**-0.00068777**	**-0.00068141**
se		0.00069421	0.00073265	0.00029101	0.00028779	0.00027726	0.00027766
t-value		2.48	2.47	-2.26	-2.33	-2.48	-2.45
p-value		**0.0379**	**0.0388**	**0.0539**	**0.0481**	**0.0381**	**0.0397**
	tue	-0.000008328	0.00002829	-0.00060575	-0.00060701	-0.00058699	-0.00058112
se		0.00028224	0.00029309	0.00020676	0.00020676	0.00020359	0.00020424
t-value		-0.03	0.1	-2.93	-2.94	-2.88	-2.85
p-value		0.9772	0.9255	0.019	0.0188	0.0204	0.0216
	wed	0.00002809	0.00021477	-0.00051958	-0.00051969	-0.00046476	-0.00045956
se		0.00019066	0.00022283	0.00016815	0.0001695	0.00016324	0.00016286
t-value		0.15	0.96	-3.09	-3.07	-2.85	-2.82
p-value		0.8865	0.3634	0.0149	0.0154	0.0216	0.0224
	thu	0.00009283	0.00030788	0.00011075	0.00009079	0.000001371	0.000008256
se		0.00018289	0.00021272	0.00020582	0.00019901	0.0001663	0.00016731
t-value		0.51	1.45	0.54	0.46	0.01	0.05
p-value		0.6254	0.1858	0.6052	0.6604	0.9936	0.9619

(continued)

	USDEURchange	-0.07510007	-0.08581895	-0.09067056	-0.0867272	-0.0833559	-0.08793817
se		0.02818039	0.02811397	0.02720458	0.0275265	0.0221903	0.03081939
t-value		-2.66	-3.05	-3.33	-3.15	-3.76	-2.85
p-value		0.0286	0.0158	0.0103	0.0136	0.0056	0.0214
	hlmean	-0.10561858	-0.11601951	-0.18055724	-0.18078696	-0.18047224	-0.18049286
se		0.01841112	0.0181861	0.0250161	0.02505804	0.02514687	0.02514517
t-value		-5.74	-6.38	-7.22	-7.21	-7.18	-7.18
p-value		0.0004	0.0002	0.0001	0.0001	0.0001	0.0001
	logreturnyesterday	0.0493306	0.04047966	0.03534896	0.03594877	0.03526719	0.03524284
se		0.01728315	0.01892246	0.01928144	0.01906182	0.01924074	0.01926483
t-value		2.85	2.14	1.83	1.89	1.83	1.83
p-value		0.0213	0.0649	0.1041	0.096	0.1042	0.1047
	vstoxxreturn	**-0.10384581**					
se		0.02043972					
t-value		-5.08					
p-value		**0.001**					
	vdaxreturn		**-0.11538869**				
se			0.02347352				
t-value			-4.92				
p-value			**0.0012**				

(continued)

	bund10return			**-0.21294895**			
se				0.07724463			
t-value				-2.76			
p-value				**0.0248**			
	bund30return				**-0.13262369**		
se					0.04704358		
t-value					-2.82		
p-value					**0.0225**		
	goldusdreturn					**0.00342535**	
se						0.01222175	
t-value						0.28	
p-value						**0.7864**	
	goldeurreturn						**0.00699416**
se							0.01157767
t-value							0.6
p-value							**0.5625**
	_cons	0.00144829	0.00145971	0.00298189	0.00299502	0.00298075	0.00297503
se		0.00038663	0.00039893	0.00035664	0.00035742	0.00035042	0.00034968
t-value		3.75	3.66	8.36	8.38	8.51	8.51
p-value		0.0057	0.0064	0	0	0.0000	0.0000
	N	41590	41590	41590	41590	41590	41590
	r2	0.24455966	0.2381704	0.03063524	0.03044485	0.02735076	0.02737316
	r2_a	0.24441431	0.23802383	0.03044874	0.03025831	0.02716363	0.02718603

Table 11. Full overview of robustness checks of the weekend effect as tested in H4 based on GARCH(1,1) model estimates (in reference to table 7)

The table below shows the conducted robustness checks of the weekend effect including coefficients, standard errors, t-values and p-values.

GARCH_Residual		Panel H1-1	Panel H1-2	Panel H2	Panel H3	Panel H4-1	Panel H4-2
	mon	**-0.00038223**		**-0.0002685**	**-0.0001758**	**-0.00072828**	
se		0.00019712		0.00018025	0.00021176	0.00027718	
t-value		-1.94		-1.49	-0.83	-2.63	
p-value		**0.0885**		**0.1747**	**0.4305**	**0.0303**	
	fri		**0.00052555**	**0.00045976**	**0.00055249**		**0.00072828**
se			0.00017821	0.00015844	0.00016076		0.00027718
t-value			2.95	2.9	3.44		2.63
p-value			**0.0185**	**0.0198**	**0.0089**		**0.0303**
	USDEURchange	-0.09164675	-0.0924955	-0.0919326	-0.0916456	-0.0916456	-0.0916456
se		0.02838609	0.02850634	0.02845013	0.02846255	0.02846255	0.02846255
t-value		-3.23	-3.24	-3.23	-3.22	-3.22	-3.22
p-value		0.0121	0.0118	0.012	0.0122	0.0122	0.0122
	GARCHcondVar	-0.06230932	-0.0603002	-0.0641881	-0.0569345	-0.05693451	-0.05693451
se		0.37578045	0.37026228	0.37157701	0.37021692	0.37021692	0.37021692
t-value		-0.17	-0.16	-0.17	-0.15	-0.15	-0.15
p-value		0.8724	0.8747	0.8671	0.8816	0.8816	0.8816

(continued)

	tue				-0.0001194	-0.00067186	0.00005642
se					0.00014034	0.00021512	0.00014151
t-value					-0.85	-3.12	0.4
p-value					0.4197	0.0142	0.7006
	thu				0.00040184	-0.00015064	0.00057763
se					0.00016146	0.00015688	0.00023487
t-value					2.49	-0.96	2.46
p-value					0.0376	0.365	0.0394
	wed					-0.00055249	0.00017579
se						0.00016076	0.00021176
t-value						-3.44	0.83
p-value						0.0089	0.4305
	_cons	-0.00033184	-0.0005117	-0.0004451	-0.0005393	0.0000132	-0.00071507
se		0.0000925	0.00007306	0.00008742	0.00013285	0.00017159	0.00015173
t-value		-3.59	-7	-5.09	-4.06	0.08	-4.71
p-value		0.0071	0.0001	0.0009	0.0036	0.9406	0.0015
	N	41590	41590	41590	41590	41590	41590
	r2	0.00198127	0.00209458	0.00215236	0.0023144	0.0023144	0.0023144
	r2_a	0.00190927	0.00202259	0.00205638	0.00217045	0.00217045	0.00217045

Table 12. Full overview of the weekend effect analysis incl. month dummies

The table below shows the weekend effect analysis under consideration of month dummies including coefficients, standard errors, t-values and p-values.

logreturn		Panel H1-1	Panel H1-2	Panel H2	Panel H3	Panel H4-1	Panel H4-2
	mon	**-0.0003996**		**-0.00030347**	**-0.00018249**	**-0.00069336**	
		0.0001988		0.00017908	0.00020878	0.00028598	
		-2.01		-1.69	-0.87	-2.42	
		0.0793		**0.1286**	**0.4075**	**0.0416**	
	fri		**0.00046269**	**0.00038827**	**0.00051087**	**0.00069336**	
se			0.00018389	0.00016169	0.00016936	0.00028598	
t-value			2.52	2.4	3.02	2.42	
p-value			**0.036**	**0.0431**	**0.0166**	**0.0416**	
	USDEURchange	-0.083309	-0.08420286	-0.08353456	-0.08314216	-0.08314216	-0.08314216
se		0.0277628	0.02786862	0.02782466	0.02782753	0.02782753	0.02782753
t-value		-3	-3.02	-3	-2.99	-2.99	-2.99
p-value		0.0171	0.0165	0.017	0.0174	0.0174	0.0174
	hlmean	-0.1757127	-0.17531511	-0.17544807	-0.17577405	-0.17577405	-0.17577405
se		0.0327089	0.03269077	0.0326652	0.03268991	0.03268991	0.03268991
t-value		-5.37	-5.36	-5.37	-5.38	-5.38	-5.38
p-value		0.0007	0.0007	0.0007	0.0007	0.0007	0.0007
	logreturnyesterday	0.0146689	0.01440023	0.01453066	0.01445516	0.01445516	0.01445516
se		0.0178364	0.01780372	0.01783621	0.01780736	0.01780736	0.01780736
t-value		0.82	0.81	0.81	0.81	0.81	0.81
p-value		0.4347	0.442	0.4388	0.4404	0.4404	0.4404

(continued)

	tue				-0.00012206	-0.00063293	0.00006043
se					0.00012808	0.00020824	0.00014206
t-value					-0.95	-3.04	0.43
p-value					0.3685	0.0161	0.6817
	wed					-0.00051087	0.00018249
se						0.00016936	0.00020878
t-value						-3.02	0.87
p-value						0.0166	0.4075
	thu				0.00049257	-0.0000183	0.00067506
se					0.00019231	0.00017615	0.0002416
t-value					2.56	-0.1	2.79
p-value					0.0336	0.9198	0.0234
	_cons	0.0044305	0.00424201	0.00432954	0.0042136	0.00472448	0.00403111
		0.0017472	0.00179087	0.00176236	0.00172367	0.00170568	0.00187186
		2.54	2.37	2.46	2.44	2.77	2.15
		0.0349	0.0453	0.0395	0.0403	0.0243	0.0634
	MONTH DUMMIES	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
	N	41590	41590	41590	41590	41590	41590
	r2	0.0473904	0.04743834	0.04751184	0.04774116	0.04774116	0.04774116
	r2_a	0.042255	0.04230318	0.04235392	0.04253819	0.04253819	0.04253819

Table 13. Heteroscedasticity and autocorrelation tests

The following table displays the conducted Breusch-Pagan (1979) and Cook–Weisberg (1983) heteroscedasticity tests and Cumby-Huizinga (1992 and 1990) autocorrelation tests based on the respective model specifications used in the weekend effect analysis.

In reference to Panel H1-1 model specification

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: mon USDEURchange hlmean logreturnyesterday 1b.ID 2.ID 3.ID 4.ID 5.ID 6.ID 7.ID 8.ID 9.ID

chi2(12) =101708.26
Prob > chi2 = 0.0000

Cumby-Huizinga test for autocorrelation
H0: variable is MA process up to order q
HA: serial correlation present at specified lags >q

H0: q=0 (serially uncorrelated) H0: q=specified lag-1
HA: s.c. present at range specified HA: s.c. present at lag specified

lags	chi2	df	p-val	lag	chi2	df	p-val
1 - 1	0.050	1	0.8228	1	0.050	1	0.8228
1 - 2	1.108	2	0.5745	2	1.012	1	0.3144
1 - 3	2.408	3	0.4922	3	0.690	1	0.4061
1 - 4	5.770	4	0.2170	4	3.650	1	0.0561

Test allows predetermined regressors/instruments
Test requires conditional homoscedasticity

In reference to Panel H1-2 model specification

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fri USDEURchange hlmean logreturnyesterday 1b.ID 2.ID 3.ID 4.ID 5.ID 6.ID 7.ID 8.ID 9.ID

chi2(12) =101598.53
Prob > chi2 = 0.0000

Cumby-Huizinga test for autocorrelation
H0: variable is MA process up to order q
HA: serial correlation present at specified lags >q

H0: q=0 (serially uncorrelated) H0: q=specified lag-1
HA: s.c. present at range specified HA: s.c. present at lag specified

lags	chi2	df	p-val	lag	chi2	df	p-val
1 - 1	0.027	1	0.8703	1	0.027	1	0.8703
1 - 2	1.032	2	0.5969	2	0.971	1	0.3245
1 - 3	2.206	3	0.5307	3	0.658	1	0.4173
1 - 4	5.588	4	0.2321	4	3.639	1	0.0564

Test allows predetermined regressors/instruments
Test requires conditional homoskedasticity

In reference to Panel H2 model specification

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: mon fri USDEURchange hlmean logreturnyesterday 1b.ID 2.ID 3.ID 4.ID 5.ID 6.ID 7.ID 8.ID 9.ID

chi2(13) =101715.77
Prob > chi2 = 0.0000

Cumby-Huizinga test for autocorrelation
H0: variable is MA process up to order q
HA: serial correlation present at specified lags >q

H0: q=0 (serially uncorrelated) H0: q=specified lag-1
HA: s.c. present at range specified HA: s.c. present at lag specified

lags	chi2	df	p-val	lag	chi2	df	p-val
1 - 1	0.058	1	0.8095	1	0.058	1	0.8095
1 - 2	1.092	2	0.5794	2	0.985	1	0.3209
1 - 3	2.314	3	0.5098	3	0.630	1	0.4275
1 - 4	5.762	4	0.2176	4	3.738	1	0.0532

Test allows predetermined regressors/instruments
Test requires conditional homoskedasticity

In reference to Panel H3 model specification

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: mon tue thu fri USDEURchange hlmean logreturnyesterday 1b.ID 2.ID 3.ID 4.ID 5.ID 6.ID 7.ID 8.ID 9.ID

chi2(15) =101747.96
Prob > chi2 = 0.0000

Cumby-Huizinga test for autocorrelation
H0: variable is MA process up to order q
HA: serial correlation present at specified lags >q

H0: q=0 (serially uncorrelated)	H0: q=specified lag-1
HA: s.c. present at range specified	HA: s.c. present at lag specified

lags	chi2	df	p-val	lag	chi2	df	p-val
1 - 1	0.038	1	0.8455	1	0.038	1	0.8455
1 - 2	1.011	2	0.6032	2	0.934	1	0.3339
1 - 3	2.152	3	0.5414	3	0.615	1	0.4330
1 - 4	5.645	4	0.2273	4	3.761	1	0.0525

Test allows predetermined regressors/instruments
Test requires conditional homoskedasticity

In reference to Panel H4-1 model specification (Panel H4-2 yields equal outputs)

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: mon tue wed thu USDEURchange hlmean logreturnyesterday 1b.ID 2.ID 3.ID 4.ID 5.ID 6.ID 7.ID 8.ID 9.ID

chi2(15) =101747.96
Prob > chi2 = 0.0000

Cumby-Huizinga test for autocorrelation
H0: variable is MA process up to order q
HA: serial correlation present at specified lags >q

H0: q=0 (serially uncorrelated) H0: q=specified lag-1
HA: s.c. present at range specified HA: s.c. present at lag specified

lags	chi2	df	p-val	lag	chi2	df	p-val
1 - 1	0.038	1	0.8455	1	0.038	1	0.8455
1 - 2	1.011	2	0.6032	2	0.934	1	0.3339
1 - 3	2.152	3	0.5414	3	0.615	1	0.4330
1 - 4	5.645	4	0.2273	4	3.761	1	0.0525

Test allows predetermined regressors/instruments
Test requires conditional homoskedasticity

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