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Daylight Saving Time and Stock Market Returns: Evidence from the Visegrad Group

Master's thesis

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Declaration of Authorship

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Abstract

Do investors make bad decisions following the clock change? If so, there would be traces of such anomaly in market data. In this thesis, we investigate these traces focusing on the stock markets of the Visegrad Group, known to be prevailingly illiquid. We combine the most recent financial data with the ARIMA-GARCH framework while employing brand-new Bayesian techniques. Using several robustness checks, we show that such effect cannot be traced in these markets. While we do not claim to challenge the seminal works in this field, we do support the evidence that the effects of daylight saving policy do not pertain to less liquid markets.

JEL Classification	C11, G12, G14, G41
Keywords	daylight saving time, market anomaly, Visegrad Group, Bayesian analysis

Title	Daylight Saving Time and Stock Market Returns: Evidence from the Visegrad Group

Abstrakt

Robia investori po zmene času zlé rozhodnutia? Ak áno, stopy tejto anomálie by boli v dátach z trhu. V tejto diplomovej práci skúmame práve tieto stopy so zameraním na akciové trhy Vyšehradskej skupiny, o ktorých je známe, že sú prevažne nelikvidné. Kombinujeme najnovšie finančné dáta s ARIMA-GARCH rámcom, zároveň používame úplne novú Bayesovskú techniku. Pomocou niekoľkých kontrol robustnosti ukazujeme, že na týchto trhoch nie je možné vysledovať takúto anomáliu. Aj keď netvrdíme, že sme spochybnili kľúčové práce v tejto oblasti, podporujeme dôkazy o tom, že účinky politiky letného času sa netýkajú menej likvidných trhov.

Klasifikace JEL	C11, G12, G14, G41
Klíčová slova	letný čas, tržná anomália, Vyšehradská skupina, Bayesovská analýza

Název práce	Letný čas a výnosy akciového trhu: Dôkazy z Vyšehradskej Skupiny

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Acronyms

ACF Autocorrelation Function

AIC Akaike Information Criterion

ARCH Autoregressive Conditional Heteroskedasticity

ARIMA Autoregressive Integrated Moving Average

BIC Bayesian Information Criterion

BUX Budapest Stock Exchange Index

DST Daylight Saving Time

GARCH Generalized Autoregressive Conditional Heteroskedasticity

MCMC Markov Chain Monte Carlo

MLE Maximum Likelihood Estimation

PACF Partial Autocorrelation Function

PX Prague Stock Exchange Index

SAX Slovakian Stock Exchange Index

WIG Warsaw Stock Exchange Index

Master's Thesis Proposal

Author	Bc. Peter Kúdeľa
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Proposed topic	Daylight Saving Time and Stock Market Returns: Evidence from the Visegrad Group

Motivation According to the efficient market hypothesis (EMH), a market is efficient if prices reflect all relevant available information (Fama 1970). If all available information is already reflected in the prices, no one should be able to predict the behavior of future price movements. Any predictable pattern of returns is a violation of the efficient market hypothesis. Numerous studies have challenged the EMH by documenting such patterns and behavioral biases in investors decision making. Seasonal patterns such as January effect (Ariel, 1987), Monday effect (French 1980), Weekend effect (Thaler, 1987) and Halloween effect (Bouman & Jacobsen, 2002) have been observed on the stock market returns. Dichev & Janes (2003) investigated the effect of the lunar cycle where stock returns were substantially higher around new moon compared to full moon dates. Weather patterns have been also investigated by Hirshleifer & Shumway (2003), Loughran & Schultz (2004), Kamstra et al. (2003) and Saunders (1993). Interestingly, Edmans et al. (2007), Geyer-Klingeberg et al. (2017) reported decline in the stock returns caused by loss of the national soccer teams in international tournaments. One of such seemingly unrelated events to changes in market prices is the daylight saving time phenomenon.

Daylight saving time (DST) policy, which represents a change of clocks observed twice a year, has been associated with severe sleep disrupting patterns (Harrison, 2013; Kantermann et al., 2007). Such sleep imbalances affect the circadian rhythm and cognitive processes of a person, leading to errors in judgement, impatience, or inattention reflected in poor investment decisions. Some literature provides such evidence: Kamstra et al. (2000) and their rebuttals (Kamstra et al. 2002, 2013) argued that DST changes are associated with significantly lower returns on US, UK, and Canadian markets following the time change. Muller et al. (2009), however, studying nine European markets found the effect to be too small to matter. In a similar vein, Gregory-Allen et al. (2010) analyze 22 different world markets, including US, Europe and Australia, rejecting the conclusions that DST affects the stock price. Siganos (2019) suggests that such effects do exist for US investors trading in firms targeted for mergers.

Even though the seminal work of Kamstra (2000) suggests the effect is highly economically relevant, the evidence from a literature is both scarce and rather contradictory. As of today, all EU members synchronize their clocks twice a year; although recently, the European Parliament endorsed a proposal to stop the seasonal clock changes starting in 2021 (EC, 2019). The evidence of the policy's side-effects related to the European markets is, however, incomplete, especially when it comes to the smaller, less liquid markets.

Hypotheses

> Hypothesis #1: Daylight saving time leads to a predictable pattern in stock market after the time change.
>
> Hypothesis #2: The effect of DST on the stock market returns is negative and more significant for the spring time change than for the autumn time change.
>
> Hypothesis #3: Target firms in M&A have higher returns on stock markets as a result of overreaction of investors.

Methodology I will test the weak-form EMH using historical market data. I will take the firm-level financial data (such as pricing factors, etc.) and market indices (such as PAX, SAX, WIG, BUX) from the Thomson Reuters Eikon database, and the weather data from National Centers for Environmental Information.

Based on the collected data I will decide on the methodologies that would fit the purpose of the study. A assume the effect of the DST on the stock market returns and volatility to be estimated using GARCH-type models. As the daylight saving time occurs only twice a year, I expect the sample to be too small. Therefore, Bayesian estimation should address this issue and enable small sample results (Ardia & Hoogerheide, 2010). Moreover, frequent issue with time series models is the overfitting, especially when one estimates a model with large numbers of parameters over a shorter time period. I thus prefer using Bayesian framework to time-series since it allows to impose certain priors on estimated parameters and to incorporate uncertainty in our parameters whenever fit. Robustness checks could be performed using outlier robust estimation with ARIMA-GARCH estimated by maximum likelihood technique standardly used for analyzing returns and volatility in finance.

Expected Contribution To the best of my knowledge, there is no empirical evidence of impact of the DST on the stock market returns in the area of Visegrad Group. The main contribution will thus be an analysis using previously not analyzed data and state-of-art methods to further enlarge the literature in the topic of stock market anomalies and effects of the daylight saving time.

Outline

1. Introduction
2. Literature review (Introduction to efficient market hypothesis, critique of EMH and literature review of market anomalies, brief introduction to DST and literature review focusing on the impact of DST on stock market returns and volatility)
3. Data (description of the data and summary statistics)
4. Methodology (ARIMA-GARCH using Bayesian estimation, robustness checks using ARIMA-GARCH maximum-likelihood estimation)
5. Results and Discussion (Effect of the DST on stock market returns and volatility, results of robustness checks, discussion of results in the context of EMH)
6. Conclusion

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Chapter 1

Introduction

The efficient market hypothesis, originally introduced by Malkiel & Fama (1970), states that market share prices reflect all the available information, leaving no room for arbitrage. If one can identify an anomaly pattern that predicts the prices, however, arbitrage does happen. These anomalies have been documented throughout the last decades. The most profound ones relate to behavioural patterns in several forms. Calendar anomalies such as the Monday effect (Thaler 1987) and the January effect (French 1980) are well-known phenomena in the financial markets. Furthermore, sports sentiment (Edmans *et al.* 2007) and weather (Saunders 1993) were found to impact investors' mood and hence financial markets. Investigation of such patterns and exploring new ones has important social welfare implications. Moreover, as Fama (1998) puts it: "dredging for anomalies is a rewarding occupation".

This thesis focuses on market anomaly related to the daylight saving time (DST) policy, which is possibly among the most controversial behavioural patterns. The policy was originally introduced to decrease energy consumption by better utilization of sunlight (Kudela *et al.* 2020). Shifting the clock twice a year, we lose one hour of sleep during the spring and gain one during the autumn. Many suggest that this transition disrupts human biorhythm, and fatigue and loss of vigilance are persistent for some time after the transition (Harrison 2013a; Kantermann *et al.* 2007). Thus, DST can change investor's behaviour, and many claim it does. The seminal work of Kamstra *et al.* (2000), for example, estimates this effect at 200% loss in returns directly after the shift compared to the average negative Friday-Monday returns. However, many studies found the effect to be too small to matter (Müller *et al.* 2009; Gregory-Allen *et al.* 2010).

While the literature focuses on the liquid market indexes such as S&P500 in the US and DAX in Germany, the DST impact on the stock market returns has not been investigated yet in less liquid markets such as those in Visegrad Group. The current thesis aims to bridge this gap in the literature. We investigate the DST effect over the period from 2000 to 2020 on the following indexes: BUX for Hungary, PX for the Czech Republic, SAX for Slovakia, and WIG for Poland. All investigated countries use the DST policy in the same form during the investigated period. Visegrad Group countries shift their clock one hour forward on the last Sunday in March and one hour backwards on the last Sunday in October.

We model the DST effect on the stock market returns using the ARIMA-GARCH framework with several specifications. These variations of the model allow us to investigate specific aspects of the DST. Deploying the different the specifications, we distinguish between the overall, spring, and autumn DST effect during the week following the DST transitions. Moreover, we capture the DST effect on the specific days within the week following both spring and autumn transitions. Furthermore, the previous literature estimates the ARIMA-GARCH models with the maximum likelihood estimation technique. Due to increasing computing power, we can tackle the estimation of the ARIMA-GARCH models using the Bayesian approach and employ the Markov Chain Monte Carlo method. Following Nakatsuma (2000) theoretical framework, we build the code for the Bayesian estimation. By pioneering the Bayesian approach to ARIMA-GARCH models in the topic of DST, we further enlarge the literature and add robustness to the results.

We find no statistically significant effects of the DST during the week after the transition regardless of the type of transition (i.e. overall, spring, autumn). Also, we do not find statistically significant differences in the intra-week effects of the DST. Our findings support the opponents of the DST policy as a market anomaly (Pinegar 2002; Lamb *et al.* 2004; Müller *et al.* 2009; Berument *et al.* 2010). Moreover, the choice of the Bayesian estimation seems to add another robustness to our results and arguably provide a better fit for ARIMA-GARCH models in terms of likelihood than maximum likelihood estimation.

The thesis is structured as follows. Chapter 2 provides the background and motivation. Firstly, we present an overview of the existing literature regarding behavioural patterns with a specific focus on the DST. Then the background of DST policy in the Visegrad Group and our motivation is presented. The description of the initial dataset and returns constructions follows in Chapter

3. Chapter 4 formally introduces the estimation framework employed. Chapter 5 summarizes the results and robustness checks. Lastly, Chapter 6 concludes the findings.

Chapter 2

Background and Motivation

This chapter provides the background and motivation behind this thesis. The first section provides the literature review of the behavioural patterns, also called market anomalies, that have been observed since the 1970s. Then, section 2.2 focuses specifically on the review of papers regarding the DST policy's impact on human behaviour and its effect on the stock market returns and volatility. The third section introduces the daylight saving time policy in the Visegrad Group. The last part presents the motivation and formulation of our hypotheses.

2.1 Behavioural patterns in stock markets

According to the efficient market hypothesis (EMH), a market is efficient if prices reflect all relevant available information (Malkiel & Fama 1970). There are three forms of the efficient market hypothesis: weak, semi-strong, and strong. The three forms differ in the information set considered to be reflected in prices. The weak form assumes only the historical evolution of prices to be incorporated in the prices. Under the weak form, profit cannot be made by following technical analysis of past prices or returns. The semi-strong form builds upon the weak form by incorporating all publicly available relevant information at the given time. For example, this information might be the current situation in the company or the economy. The strong form states that both public and private information relevant to prices is already included in the prices. If all available information is already reflected in the prices, no one should predict the behaviour of future price movements. If we find any predictable pattern of returns, the efficient market hypothesis is violated.

Numerous studies have challenged the EMH by documenting patterns that predict price movement and behavioural biases in investors' decision making. Seasonal patterns such as Monthly effect (Ariel 1987), Monday effect (French 1980), January effect (Thaler 1987) and Halloween effect (Bouman & Jacobsen 2002) have been observed on the stock market returns already several decades ago. The monthly effect is an anomaly in the stock index returns with a monthly pattern. Stocks seem to yield positive average returns only around the beginning of the calendar year or within the first six months of a calendar year and zero average returns after the first half of the year. Specifically, the average monthly return of an equal-weighted index of the New York Stock Exchange (NYSE) was approximately 3.5 % in January, while the average during other months was only 0.5 % over the period 1904-1974. Several other phenomena, such as higher returns for small firms and dividend-related excess returns, are concentrated in January. Even though this anomaly is quite significant, it is hard to leverage this in a trading strategy for a regular investor as the transaction costs and bid-ask spread mitigate the profit potential (Ariel 1987). Bouman & Jacobsen (2002) reported a statistically significant difference between the May-October period and the rest of the year. For the May-October period, the returns seem to be negative or not different from zero. In contrast, the November-April period is found to be positive on average. The results hold after accounting for the January effect and other robustness checks.

Other examples of the calendar anomalies besides the monthly patterns are the ones occurring within a week. The Monday effect, also called the Weekend effect, is an anomaly of the average daily returns on Monday being negative. French (1980) studied the Standard and Poor's composite portfolio during the period from 1953 to 1977 to test for the presence of the Monday effect. For the majority of the investigated period, the average return on Monday was found significantly negative. On the other hand, the average returns that occurred during the following days of the week were found positive.

Another calendar anomaly is connected to the holidays. Investors and, therefore, also markets are affected by the disruptions in the working days. Holiday effect (Ariel 1990) and Halloween effect (Bouman & Jacobsen 2002; Cadsby & Ratner 1992) were investigated to shed more light on calendar anomalies. Ariel (1990) investigated the behaviour of the US stock market returns around the holidays during the period from 1963 to 1982. The results indicate that, on average, the return on days preceding the holiday equal nine to fourteen times the returns on other days. Cadsby & Ratner (1992) further supported the findings and confirmed the presence of the holiday effect for the US, Canada, Japan, Hong Kong and Australia. As the results suggest that the holiday effect is present also in other countries than the US, it is not solely a result of 'mining' the US stock market data to find any pattern, and clearly, there is some rationale behind this effect. In Europe, however, the holiday effect is not present.

Besides calendar anomalies, Dichev & Janes (2003) studied possible lunar cycle anomalies in the US and other 24 countries. Results indicate that the stock returns are approximately double around the new moon days compared to the full moon days. The effect was found significant for the US stock market during the period between 1910 and 2002. For other countries, it was found significant in the period 1972 to 2002. On the other side, return volatility, the volume of trading and bond returns seem to be unaffected by the lunar cycle.

Apart from the anomalies above, there is also broad literature capturing another factor that may influence the investors' behaviour and thus the markets - the weather. Weather patterns have been studied by Hirshleifer & Shumway (2003), Loughran & Schultz (2004), Kamstra *et al.* (2003) and Saunders (1993). Hirshleifer & Shumway (2003) studied the effect of the weather conditions on 26 stock markets internationally in the period from 1982 to 1997. Intuitively as the sun affects the mood of investors positively, sunshine is significantly positively correlated with stock returns. On the other hand, rain and snow are not found to have an effect on the stock returns after controlling for sunshine. The implications of these findings in terms of profitability are not significant as transaction costs again mitigate the profit potential. However, these results could remind the investors to be aware of their mood before making a decision (Hirshleifer & Shumway 2003).

Saunders (1993) further questions the efficiency of the market with respect to weather conditions by conducting robustness checks on the local effect of the New York City (NYC) weather on the NYC stock market. After accounting for other anomalies such as the January effect, the weather still influences the market. One could argue that the local weather in NYC is not a good proxy for the weather conditions as the decision to buy or sell comes from different geographical areas around the world and not only the local area of New York City. In order to account for this issue Loughran & Schultz (2004) use findings of Coval & Moskowitz (1999; 2001) and Grinblatt & Keloharju (2001) that investors trade with stocks of local companies disproportionally. This means that if the company's headquarters is in the same city as investors, the investors are more likely to buy that company's stock compared to investors in different cities. Therefore, Loughran & Schultz (2004) used data for 25 different cities. The authors found no statistically significant evidence that the company headquarters' weather affects the stock returns in all cities except for New York City, where there seem to be lower returns during cloudy days.

Kamstra *et al.* (2003) look at this issue from a different point of view. Rather than looking at the effect of the sunlight in terms of the weather being sunny or cloudy, the authors investigate the effect of the sunlight's length within a given day regardless of the weather. Specifically, the paper studies the seasonal affective disorder (SAD) that affects people during the period of a relatively lower amount of daylight. Kamstra *et al.* (2003) study the US, Sweden as northern market, and Australia as Southern Hemisphere representative. After controlling for several factors such as other anomalies and related factors, the results support the hypothesis that SAD (i.e. periods of a low amount of daylight) negatively affects the stock market returns. Moreover, the higher the latitude, the bigger the effect.

Lastly, the building block of the market's behavioural view also presented in the market anomalies above is a general idea that investors' mood affects their decision-making. Edmans *et al.* (2007), Ashton *et al.* (2011), Ehrmann & Jansen (2015), Geyer-Klingeberg *et al.* (2018) and many others studied how national sport sentiment affects individuals' mood and possibly subsequent decisions made on the stock market, therefore affecting the stock returns. Edmans *et al.* (2007) motivated by the psychological literature that found a strong relationship between national sports outcomes and people's mood and behaviour (Carroll *et al.* 2002; Hirt *et al.* 1992; Schwarz *et al.* 1987) studied the effect of international soccer results on the stock market. The authors find statistically and economically significant effect of a loss of an international soccer match on the market of the country that lost the game. The effect of winning was not statistically significant. Interestingly, Ashton *et al.* (2011) confirms the findings of Edmans *et al.* (2007) in terms of losing. Using several robustness checks such as accounting for outliers and employing GARCH, the results suggest that also winning affects the returns. Hirt *et al.* (1992) even studied the intraday data during the soccer matches that eliminated France and Italy from the 2010 FIFA World Cup. The results suggest that the countries' stock indexes were under-priced by seven basis points during the losing matches. Recently, Geyer-Klingeberg *et al.* (2018) collected the results of 37 related studies to perform a meta-analysis. The authors find severe publication bias, specifically considering the effect of a loss on the stock markets. After adjustments for the bias, the effect of losses and wins of national soccer matches on stock markets is statistically insignificant.

Most of the anomalies above generally represent events or conditions that, at first glance, seem to be unrelated to the stock market returns or volatility. When one dives deeply into the rationale behind it, such a condition or event suddenly appears relevant to the stock markets. One of such seemingly unrelated events that have not been mentioned so far and will be the main focus of this thesis is the daylight saving time. The existing literature regarding daylight saving time follows.

2.2 Behavioral patterns due to daylight saving time

Many studies suggest undesirable impacts of the DST policy on people's sleeping patterns affecting their biorhythm, sleep, health, and ability to focus, thus affecting their behaviour following both the spring and the autumn change (Barnes & Wagner 2009; Robb & Barnes 2018; Coren 1996; Harrison 2013b). Harrison (2013b) pointed out that sleep fragmentation and sleep loss happen both during the spring and autumn transition. Additionally, Janszky *et al.* (2012) connected the sleeping pattern's disruption, after the spring DST change, with health-related issues, specifically higher occurrence of acute myocardial infarction.

Other consequences of the negative effect of the DST change on people sleep disturbance may be lowering their ability to focus. Coren (1996) suggests an 8% increase in traffic accidents attributable to the spring DST change in Canada. Barnes & Wagner (2009) found the sleep deprivations due to the DST change to increase the number of work-related injuries. Robb & Barnes (2018) further support the evidence for work injuries (marginal increase) and traffic accidents (16% increase) during the DST transition. Interestingly, he finds a lower number of household accidents and argues that people may anticipate a riskier period and raise their awareness. On the other hand, conflicting results are reported by Holland & Hinze (2000); Huang & Levinson (2010). They found no statistically significant DST results on workplace injuries and or car accidents, pointing out precisely the fact mentioned above that people anticipate the riskier period and pay more attention. Moreover, an additional hour of daylight in the evening during the spring transition was associated with fewer accidents.

DST policy might affect human behaviour as the sleep disturbance is evident and significant during the transition period (Harrison 2013b). Therefore, one can argue that this disturbance could affect people's decision-making, thus affecting their life and work-related decisions. As investors are also human beings, one could question the efficiency of the stock market as there is a possibility that during DST transitions, investors' decision-making is affected and may lead to predictable patterns in stock prices. Generally, the literature on the effect of the DST on the stock market returns and volatility is divided into proponents of the significant effect of the DST and opponents that find a null or negligible effect. Furthermore, the discussion regarding the proper methodology that should be used is still ongoing. Thus, we present the papers in chronological order to demonstrate the evolution of the discussion regarding the correct estimation framework and results.

The first and the most visible proponents of the DST effect on the stock market have been Kamstra *et al.* (2000). The authors were the first to investigate the DST effect on US stock market indices, namely S&P500 and both value and equally weighted indices of NYSE, AMEX, NASDAQ. Canadian stock market (TSE300), UK stock market (UK total market), and German stock market (DAX100) were investigated, too. Using maximum likelihood estimation of the AR(1)-GARCH(1,1) model, the authors estimated the effect of DST on return by focusing on the first trading day following the DST change. They found a statistically and economically significant effect of the DST transition period on stock market returns for both spring and autumn change. Authors found a larger negative return with a magnitude between two to five times larger than the average return during the weekends when DST change did not happen. The effect was statistically significant for all market indices except for Germany.

Pinegar (2002) was one of the first to question the findings of Kamstra *et al.* (2000). His paper argues that Kamstra *et al.* (2000) results are not robust and provides further robustness checks. The author shows detailed results for the US stock market spring, fall, and total (spring and autumn combined) DST effect and finds a statistically significant difference in DST returns only for the autumn change and total change. Moreover, the author suggests that the difference is driven by the two outliers representing stock market crashes during the investigated period. Additionally, heteroskedasticity adjustments that account for these outliers mitigate the statistical significance of the autumn difference. Classical fixed-level hypothesis tests suggest that the total difference remains statistically significant for some indexes even after the heteroskedasticity adjustments. However, the Bayesian posterior odd ratio indicates no effect of DST on the stock market returns. The author also fails to reject that DST weekend and non-DST weekend returns have the same distribution and thus conclude that there is no statistically significant DST effect.

In the following paper, Kamstra *et al.* (2002) turns Pinegar (2002) arguments against him by stating that the author ignores international evidence, misinterprets the results, performs several invalid tests, and systematically understates the statistical significance of the valid tests. More specifically, by international evidence Kamstra *et al.* (2002) refer to the effect of DST in Germany, the UK and Canada. Following that, Lamb *et al.* (2004) re-examine the DST effect in the US stock market on the same sample as Kamstra *et al.* (2002) and find no statistical evidence of the effect contributing to the opponents of DST anomaly.

To contribute to the topic outside of the US stock market, Worthington (2003) investigate the DST effect on the Australian Stock Exchange. Combining the methodology of both Pinegar (2002) and Kamstra *et al.* (2000) the author divides the returns of the stock market index into weekend returns when DST occurred during the weekend, weekend returns when DST did not occur during the weekend, and day-of-the-week returns. The author faces additional issues compared to the previous papers as not all Australia's regions experienced the DST or some of the regions cancelled and reintroduced the DST over the studied period from January 1980 to May 2003. To account for these differences, the identification consists of two sets of starting dates and three sets of ending dates. Worthington (2003) finds the coefficient of the spring DST change to have an economically negative effect (lower returns), and autumn DST change to have an economically positive effect (higher returns). However, after the adjustment for heteroskedasticity and autocorrelation, the effect is not statistically significant, further supporting the conclusions of the Pinegar (2002) and Lamb *et al.* (2004).

Müller *et al.* (2009) provides a comprehensive analysis of the DST effect on the German market and analysis of country portfolios representing Northern, Southern and Central Europe that support findings of Pinegar (2002). No statistically significant effect of the DST on stock market returns is found in these markets over the overall investigated period from January 1980 to June 2007. Interestingly author suspects that the DST effect could be already incorporated by the agents in the market, and therefore divides the period into 5-year sub-samples. Keeping in mind that these sub-samples consists of a very low amount of observations, 5 to 10 depending on specifications, Müller *et al.* (2009) finds evidence of the DST effect in the earlier periods with diminishing pattern in significance. Moreover, the paper suggests that even the weekend effect is diminishing over time, thus indicating that the efficiency of the German market and representatives of Northern, Southern and Central Europe was increasing over time.

Gregory-Allen *et al.* (2010) further enlarges the evidence that opposes Kamstra *et al.* (2000) by investigating 22 countries globally from the US to Hong Kong. The authors use a similar model specification to Kamstra *et al.* (2000). As the returns are usually leptokurtic, the normality assumption is violated. Therefore, the authors use Newey-West robust standard errors as they are robust to an unspecified form of heteroskedasticity and autocorrelation. Gregory-Allen *et al.* (2010) find no statistically significant evidence in the studied markets and deliver added-value by investigating more global markets over a longer time horizon employing more robust methods.

Berument *et al.* (2010) study separately the effect of spring and autumn DST change for the US stock market, similarly to Pinegar (2002) and Lamb *et al.* (2004). Moreover, as the DST affects disrupts individual circadian clock, it may also affect risk-aversion. Thus, the authors study the DST effect on the volatility by modelling the DST and Monday effect in a generalised autoregressive conditional heteroskedasticity model, specifically exponential GARCH (E-GARCH), to allow for possible asymmetry in negative and positive shocks. Contrary to Kamstra *et al.* (2000) and in line with Pinegar (2002) and Lamb *et al.* (2004), Berument *et al.* (2010) find no statistically significant results of the DST effect on returns. This finding is supplemented by volatility analysis that yields the same statistically insignificant results.

Consequently Kamstra *et al.* (2010) opposed the findings of no statistical significance of DST effect on stock market returns and volatility presented by Berument *et al.* (2010) by arguing that they do not provide a complete literature review, use highly over-parametrised estimation with E-GARCH having 15 lags in mean return equation, use estimation methods that produce biased estimates of the parameters of the mean, and that their results are not completely replicable. Additionally, Kamstra *et al.* (2010) employ several robustness checks to the Berument *et al.* (2010) results and find several inconsistencies and high differences. Next, Kamstra *et al.* (2010) argue that one should be careful when using over-parametrised models for modelling variance, even though their estimation suggested economically and statistically significant DST effect.

In the following reply, Berument & Dogan (2011) do not try to oppose Kamstra *et al.* (2010), but rather focus on a new aspect of possible DST effect on the stock market, although the paper was titled as a reply to Kamstra *et al.* (2010). Even though the results of Berument *et al.* (2010) finds no statistically significant evidence of the effect of the DST on stock market return or volatility, Berument & Dogan (2011) suggest that there may be the effect of the DST on the stock market in the relationship between stock market returns and volatility. Using E-GARCH, including the volatility relationship in the mean return equation, authors find statistically significant evidence that the return-volatility relationship changes during the DST shifts. Berument & Dogan (2011) argue that lower returns on DST can be attributable to lower pricing of volatility during the DST shifts. The findings of Berument & Dogan (2011) are seriously questioned in Kamstra *et al.* (2013) as none of the concerns raised by Kamstra *et al.* (2010) are addressed. Additionally, Berument & Dogan (2011) results contradict Berument *et al.* (2010). Thus, Kamstra *et al.* (2013) encourage readers to be skeptical about the presented results of both Berument *et al.* (2010) and Berument & Dogan (2011) .

The most recent paper by Siganos (2019) analyses the effect of DST on the stock market but from a different perspective. The author provides robust evidence that the firms' stock returns targeted for mergers are more positive following the Mondays after the DST change. Additionally, target firms' stock return volatility is higher on the first day after the DST change. This suggests that the decision-making of investors is affected by the DST as their circadian cycle experiences disruption.

This disparity between the estimation techniques and results between the authors suggests that the DST effect on the stock market needs further investigation. As most of the authors investigated major, most liquid stock markets, this paper focuses on minor, less liquid markets from the Visegrad Group. Thus, this thesis provides a unique opportunity to investigate the effect of the DST that further supports the existing literature.

2.3 Daylight saving time in Visegrad Group

Daylight saving time policy was first introduced in all Visegrad Group countries, namely the Czech Republic, Hungary, Poland and Slovakia, in 1916 during

World War I to preserve coal. Since then, DST has been on and off in the countries throughout various periods until 2020, amounting to 60 years of DST changes on average. The most recent year in which there was no DST was in 1979 in Hungary, 1978 in the Czech Republic and Slovakia, and 1976 in Poland. Our investigated period will span from 2000 until 2020. The DST changes in all countries within this time horizon coincided. Spring change occurs every last Sunday in March, and the time shifts from 2 a.m. to 3 a.m. (from UTC+1 to UTC+2). Thus, we 'lose' one hour of sleep. On the other hand, the autumn shift happens during the last Sunday of October with the time shift from 3 a.m. to 2 a.m. (from UTC+2 to UTC+1), which 'gives' us one hour of sleep.

This 7-months-long DST window for our investigated period is coherent with the common EU directive. Even though all European Union member states adjust their clocks once in spring and once in autumn following the same directive (2000/84/EC), soon it might be over (European Parliament 2019). In February 2018, citizens initiatives incentivised European Parliament (EP) to call on the European Commission (EC) to provide an assessment of the DST policy directive and, if relevant, propose the revision of the directive (European Parliament 2019). The assessment provided 4.6 million responses, out of which 84% were in favour of cancelling the DST policy. Thus, the European Commission raised a proposal to end the directive clock adjustments (European Parliament 2019). In March 2013, the European Parliament (EP) backed the proposal to end the practice of synchronising the clock twice a year in the EU. To preserve stability, EP members voted to postpone the end of the unified DST policy to 2021, giving the member states freedom to choose whether to keep, change, or cancel the DST policy.

Across the analysed period (2000-2020), the Visegrad Group countries followed the same DST policy, even before the common EU directive. Table 2.1 lists the dates of changes to DST in spring and back to standard time in autumn. An important fact is that the change always occurs during the weekend when the stock market does not operate. Therefore, one has to be cautious of the well-documented Monday (Weekend) effect.

Table 2.1: Days of the DST shift

Year	*Spring*	*Autumn*	*Year*	*Spring*	*Autumn*
2000	March 26	October 29	2011	March 27	October 30
2001	March 25	October 28	2012	March 25	October 28
2002	March 31	October 27	2013	March 31	October 27
2003	March 30	October 26	2014	March 30	October 26
2004	March 28	October 31	2015	March 29	October 25
2005	March 27	October 30	2016	March 27	October 30
2006	March 26	October 29	2017	March 26	October 29
2007	March 25	October 28	2018	March 25	October 28
2008	March 30	October 26	2019	March 31	October 27
2009	March 29	October 25	2020	March 29	October 25
2010	March 28	October 31			

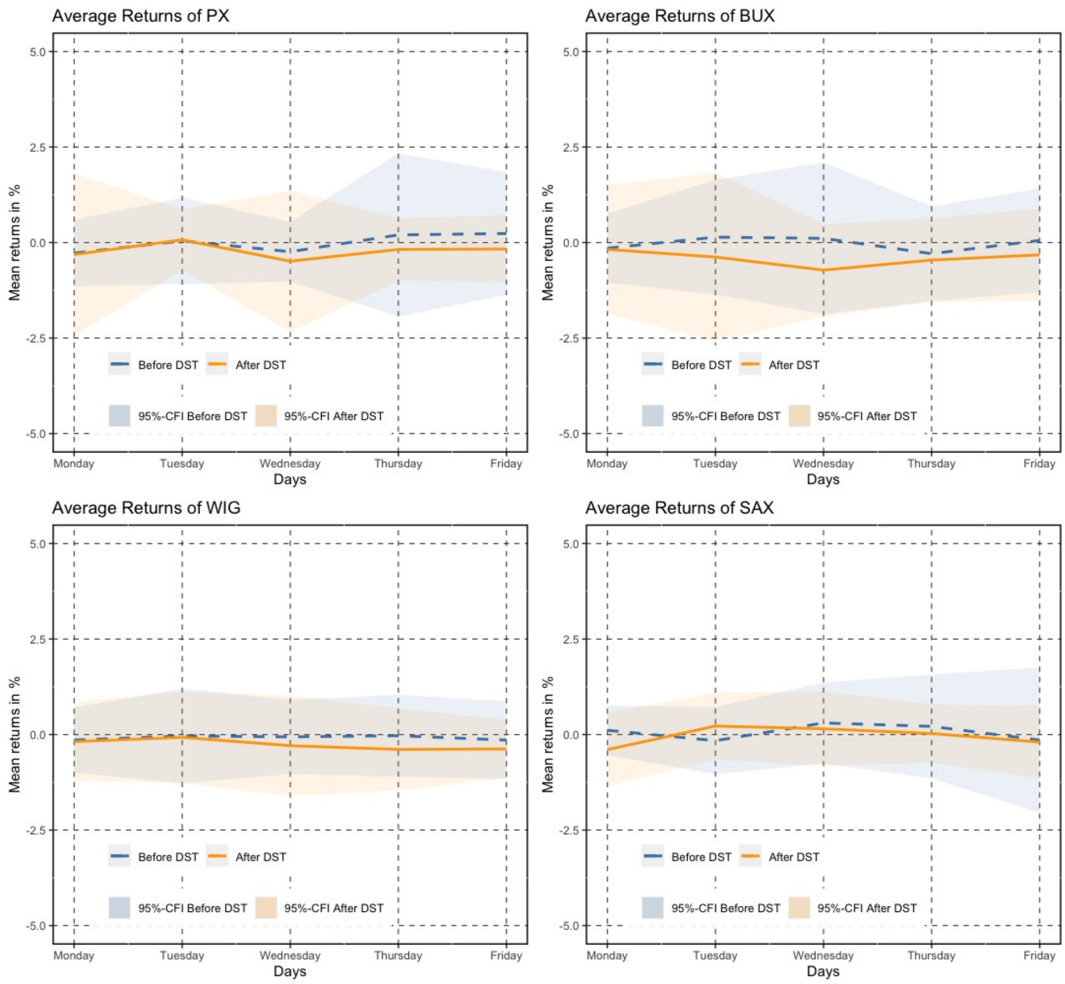
Note: Days when the all countries of the Visegrad Group shift to DST in spring and back to the standard time in autumn.

2.4 Motivation and hypotheses

According to sections above, if there is any DST effect on the stock market returns, it should occur during the first days after the transition. Because the DST policy spans across the whole investigated period, we do not have an exact control group, a year where the transition did not occur. However, one could argue that the DST effect lasts only for several days until our bodies adapt to the change. Therefore, the treatment group could be the week following the DST transition and the rest of the days could serve as a control group.

Intuitively, to visualise the DST's potential effect, Figure 2.1 compares the mean returns for each weekday in the week before and after the time shift, regardless of whether it is a spring or autumn transition. Figure 2.1 is purely for the motivation purpose and was created by averaging the returns of the week before the time change and week after the time change (further details about the data are in Chapter 3). The dashed line with the respective confidence interval represents the week before the DST and the solid line represents the week after the transition occurs. The figure provides us with several insights. Firstly, the average Monday return is negative in all cases except the week before the DST change in Slovakia. This could indicate the presence of the Monday effect, which we should include in our model. Secondly, the point estimates of the returns after the change are below the estimates before the change, indicating a possible negative DST effect on returns. Lastly, the effect of the DST might vary throughout the week.

Figure 2.1: Average Returns before and after DST transition



Note: The average returns of the stock market indexes in the Visegrad group. The averages comes from the days within one week before and after the transition aggregating the spring and autumn transition.

Hypotheses

Based on the previous literature, our intuition and simple visualisation above, we formulate the hypotheses below. Firstly, Hypotheses 1 and 2 about overall effect and spring effect are straight forward and similar to Kamstra *et al.* (2000), which test these hypotheses for S&P 500, NASDAQ, NYSE, AMEX. We expect spring transition to negatively affect the returns as the market agents are disrupted by 'losing' one hour of sleep. The same intuition applies to the overall effect as we believe that spring disruption should be more significant than autumn disruption. Hence, we anticipate the spring DST effect to offset the autumn DST effect.

> **Hypothesis 1.** *The overall effect of DST on the stock market returns is negative.*

> **Hypothesis 2.** *The spring effect of DST on the stock market returns is negative.*

The autumn effect is, however, not so straight forward. Naturally, we could believe that the opposite transitions should positively affect the market indexes. However, we might argue that even though we 'gain' an hour of sleep, it is still a disruption for our bodies to a possibly lower degree. Therefore we formulate Hypothesis 3 as follows.

> **Hypothesis 3.** *The autumn effect of DST on the stock market returns is either positive or more negligible compared to the spring effect.*

The last two hypotheses are unique, and they are not explicitly stated in the previous literature. Our intuition behind Hypothesis 4 is that we believe that the DST effect should have the highest impact on Monday since it is the first trading day following the transition that occurs during the weekend. Naturally, Hypothesis 5 follows the same logic. As we move further from the DST transition, we expect gradual adaptation of the market and diminishing effect.

> **Hypothesis 4.** *The effect of DST on the stock market returns is biggest on Monday following the change.*

> **Hypothesis 5.** *The effect of DST on the stock market returns diminishes over time.*

We will test these hypotheses using the data presented in Chapter 3 and Methodology in the Chapter 4.

Chapter 3

Data

3.1 Stock market indexes

This thesis employs daily data for countries of the Visegrad Group, namely the Czech Republic, Hungary, Poland, and Slovakia. The price history of the stock index for every country was provided by Thomson Reuters - Eikon. For Hungary, the market index of our interest is BUX, which currently consists of 16 major Hungarian companies trading on the Budapest Stock Exchange and uses free-float capitalisation weightings (Budapest Stock Exchange 2019). BUX daily closing prices span from January 2000 until January 2020.

For the Czech Republic, we focus on the PX market index, an official price index of the Prague Stock Exchange. PX is a free-float weighted price index consisting of the most liquid stocks (Prague Stock Exchange 2019). The daily closing prices were again obtained from January 2000 until January 2020.

For Poland, Warszawski Indeks Gieldowy (WIG) is used, and daily closing prices are obtained from Thomson Reuters for the same time horizon from 2000 until 2020. We have chosen this index as it is the first exchange index in Poland and has been calculated for the longest time period (GPW Benchmark S.A. 2019). WIG is a total return index. Thus it takes into account both prices of underlying shares and dividend payments. The initial value of the WIG index was 1000 points, and WIG currently consists of 336 companies (GPW Benchmark S.A. 2019).

Lastly, for Slovakia, there is a SAX index as an official stock index of the Bratislava Stock Exchange for the same period as previous indexes. SAX uses capitalisation weightings, and it is a total return index (The Bratislava Stock Exchange 2019).

In Table 3.1 you can find descriptive statistics of the daily closing prices of the indexes mentioned above.

Table 3.1: Descriptive Statistics of the closing prices

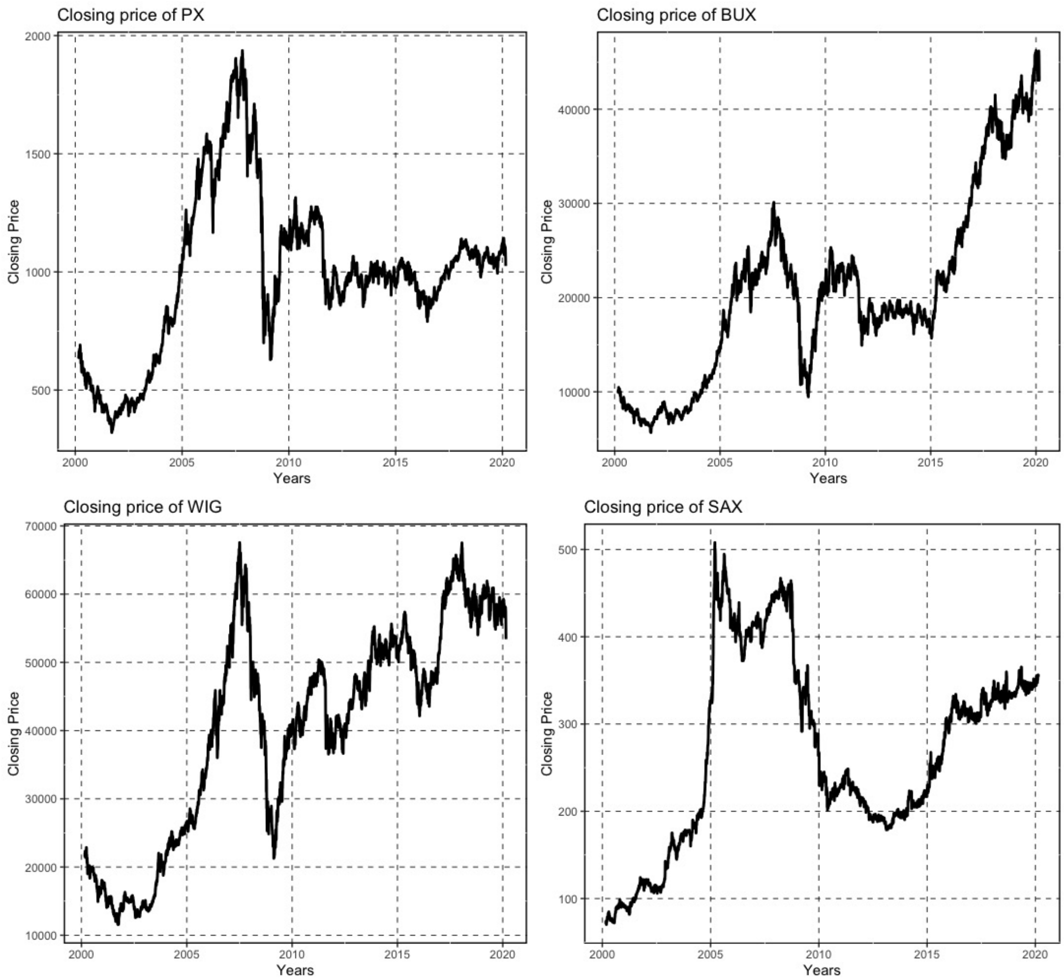
Index	*Mean*	*StDev*	*Minimum*	*Maximum*	*Observations*
SAX	265	109	70	508	4,828
PX	993	377	320	1,936	4,954
BUX	20,104	9,491	5,671	43,598	4,993
WIG	39,724	15,741	11,565	67,569	5,008

Even though it may seem that the descriptive statistics do not provide much information at first sight, they can provide at least some intuition. We can observe a significant difference in the prices as minimum and maximum are quite distant for all indexes. This is common in the financial literature, so one should rather use returns instead of prices. Despite observing exactly the same period for all countries of the Visegrad Group, Slovakia has the lowest amount of observations. This is due to the fact that Slovakia has the highest amount of holiday among countries of the Visegrad Group. The difference in the actual values between the markets is irrelevant as they will be analysed separately and using returns.

To provide basic information about what to expect about the data, Figure 3.1 depicts simple visualisation of daily prices of all four stock indexes, starting from the beginning of 2000 until the beginning of 2020. One can observe similarities across indexes over time. Figure 3.1 indicates overall growth with a significant fall around the 2008 Financial Crisis for all indexes. In the aftermath of the Financial Crisis, the graphs indicate a gradual recovery of prices and further growth for BUX and WIG. On the other hand, SAX and PX still have not reached the pre-crisis levels yet. From the first look, we could argue that there will be a serious autocorrelation in the prices as they seem to follow an increasing pattern with occasional shocks. Therefore, this work will be using daily returns instead of the closing prices, as it is the best practice in analysing the financial data.

Furthermore, stationarity is an essential property that needs to be satisfied. If the process that our data follow is not stationary, spurious regression might be a problem. The process is stationary when it has a constant and finite mean, variance, and covariance in time. Figure 3.1 indicate that the mean is not constant for neither of our stock prices. Dickey-Fuller test in Table A.17

Figure 3.1: Daily closing prices



Note: Daily closing stock prices of the market indexes in Visegrad Group from the 2000 until the beginning of 2020.

for all observed stock prices identifies the unit root, which directly implies a non-stationary process. Using returns instead of prices might solve this issue.

3.2 Returns

In the financial literature there are usually two forms of returns: discrete and continuous. In this thesis the continuous returns are analysed and they are specified by the following equation:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.1}$$

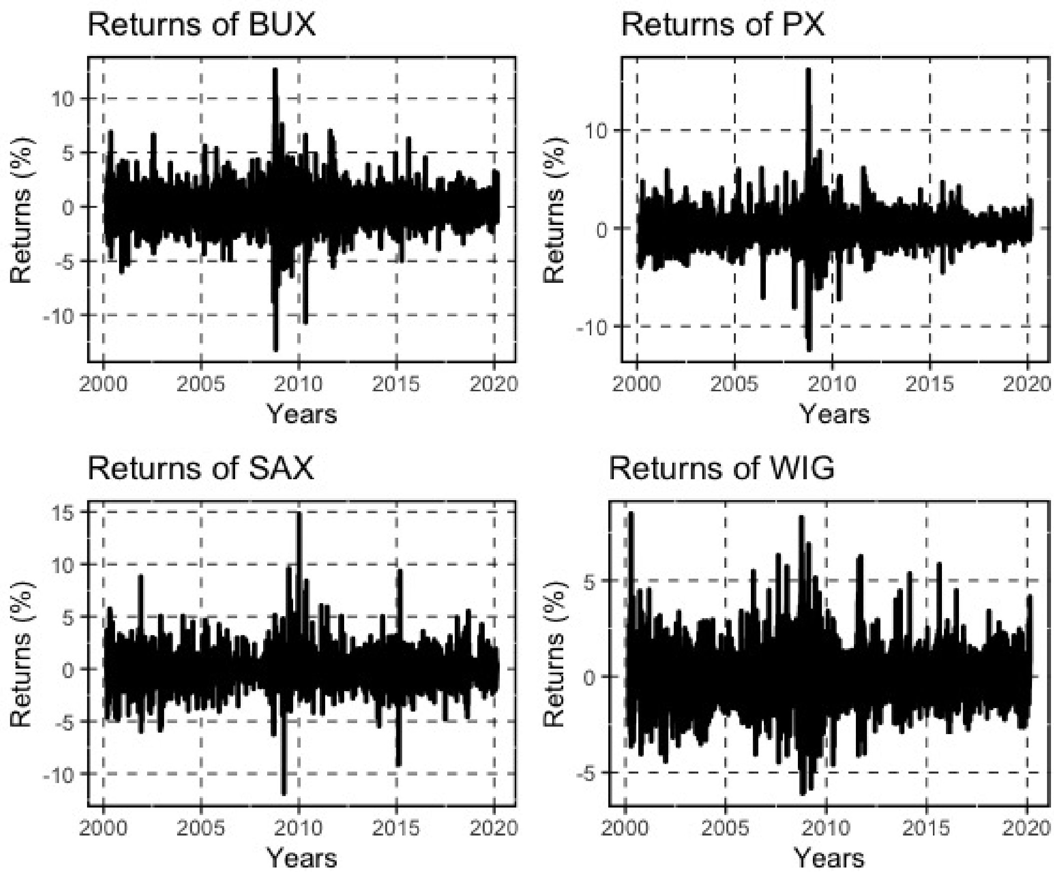
where, r_t is the return in time t, ln is the natural logarithm, P_t is price in time t, and P_{t-1} is price in previous period.

Since the stock market trading occurs only during the working days, weekend and holidays are missing the values for the prices. As the DST transition always happens during the weekend, the returns of our interest will be Monday returns or so-called 'weekend' returns. In most of the cases, the 'weekend' return is calculated using Friday and Monday prices in equation 3.1. In case that any of the holidays occur on Monday, the 'weekend' return is calculated by substituting Monday with the following day for which we have the return. For the missing Friday prices, we used the nearest preceding day.

Figure 3.2 depicts the returns over time and the histogram of the returns of all four stock indexes computed according to the equation 3.1. The presence of outliers is visible for all countries, with the most significant changes in returns around the Financial Crisis in 2008. We also observe some volatility clusters. Furthermore, the histograms suggest that the returns are skewed and have excess kurtosis compared to the normal distribution. This leptokurtic behaviour is a common feature of the financial market data.

Table 3.2 provides an overview of the descriptive statistics of the returns. We can observe that the mean return is negative but very close to 0 for all the indexes. The standard deviations range from 1.178 for SAX to 1.459 for BUX. The minimum and maximum indicate potential outliers as the values are more than quadruple the standard deviation apart from the mean. The last column shows the number of days where we do not observe a price change, and there is zero return. We should keep in mind that the SAX index stands out with 744 days with zero returns which are approximately 15% of our observations.

Figure 3.2: Daily returns

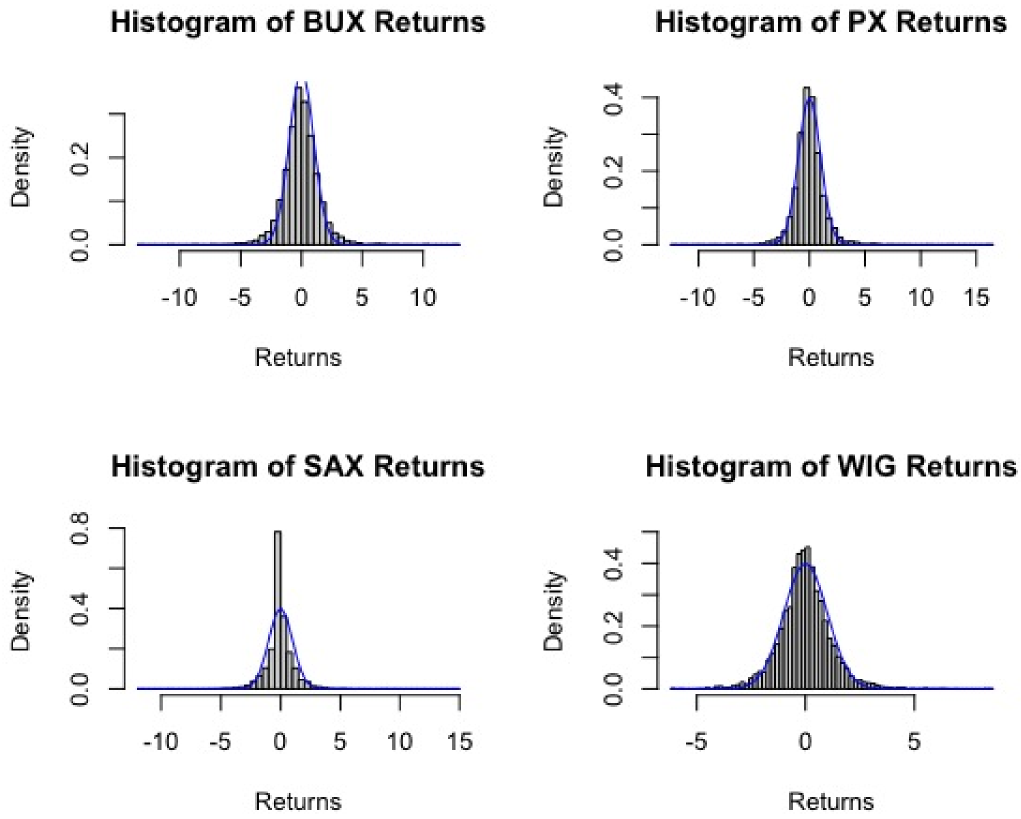


Note: Daily returns of the market indexes in the Visegrad Group from the 2000 until the beginning of 2020.

Table 3.2: Descriptive Statistics of the returns (in %)

Index	*Mean*	*StDev*	*Minimum*	*Maximum*	Days with 0% returns
BUX	-0.03	1.459	-13.178	12.649	0
PX	-0.01	1.321	-12.364	16.185	15
SAX	-0.032	1.178	-11.88	14.810	744
WIG	-0.018	1.205	-6.084	8.468	1

Figure 3.3: Histogram of daily returns



Note: Histogram of daily returns of the market indexes in the Visegrad Group from the 2000 until the beginning of 2020. The line represents density function of the standard normal distribution.

Regarding the stationarity, looking at the Figure 3.2 we can observe that taking log-returns of our prices according to the Equation 3.1 yields much better results. The returns seem to have a constant mean. The presence of the unit root is ruled out by Dickey-Fuller and Augmented Dickey-Fuller test, with the p-value being 0.01 for all returns. The variance, however, seems to be non-constant over time. Nonetheless, as we are using ARMA-GARCH (see Chapter 4) model specification, the GARCH part should capture these differences in time. As long as we satisfy $\alpha_1 + \beta_1 < 1$ we should have constant unconditional variance. Thus, taking log returns of the closing prices combined with our ARMA-GARCH model specification should secure stationarity.

Chapter 4

Methodology

This chapter is divided into two sections. The first section describes the building of the model we employ to capture the behaviour we want to estimate. The second section explains the Bayesian approach as an estimation technique for our model.

4.1 Model

4.1.1 Mean equation (ARIMAX)

The statistical model used to test our hypotheses about the effect of the DST on the returns is an ARIMAX model. This is a type of the ARIMA (p,d,q), where p is the order of the autoregressive part, q is the order of the moving average part, d is the degree of differencing and X represents inclusion of exogeneous variables. Several specification of the model are used to capture the overall effect, differences in the spring and autumn transition and differences in the effect throughout the week after the change. Using the methodology above and specification similar to the Müller *et al.* (2009) the mean return equation is expressed in four specifications 4.1, 4.2, 4.3, and 4.4. Firstly, mean model equation is presented below:

$$r_t = \beta_0 + \beta_1 DMonday_t + \beta_2 DST_t + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \tag{4.1}$$

where subscript t represent time, β_0 is a constant, $DMonday$ is the dummy variable that equals 1 for every Monday return to account for the often observed and well documented Monday effect, p and q is the order of autoregressive and moving average process, respectively. DST is a dummy variable that equals 1 in the first week following the spring and autumn DST transitions.

Secondly, daylight saving time change occurs twice a year, once we shift the clocks an hour forward (spring change) and once an hour backwards (autumn change). Naturally, the effect of DST should be investigated in these periods separately. There might be a difference in the way people adapt to different direction of the change or the season itself can have an impact on the DST effect. Mean equation 4.2 distinguishes between the spring and autumn effect:

$$\begin{aligned} r_t = \beta_0 + \beta_1 DMonday_t + \beta_2 DST_t^{spring} + \beta_3 DST_t^{autumn} + \\ + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \end{aligned} \tag{4.2}$$

where, DST_t^{spring} is a dummy variable that equals to 1 during the first week following the spring transition. Similarly, DST_t^{autumn} is a dummy for the autumn transition. Remaining variables, parameters, and subscript are the same as in the equation 4.1.

Thirdly, one could argue that the DST effect can be negligible when considering the whole week as being affected by the shift. The effect may diminish or vary the further we are from the time shift as our bodies adapt to the change. To analyse this phenomenon, equation 4.3 employs the dummy variables for each trading day in the first week following the shift.

$$\begin{aligned} r_t = \beta_0 + \beta_1 DMonday_t + \beta_2 MonDST_t + \beta_3 TueDST_t + \\ + \beta_4 WedDST_t + \beta_5 ThurDST_t + \beta_6 FriDST_t + \\ + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t \end{aligned} \tag{4.3}$$

Lastly, the change in DST effect over the week could be affected by the type of the time change or by the season itself. To account for the differences in spring and autumn over the week, the following specification is used:

$$
\begin{aligned}
r_t = \beta_0 &+ \beta_1 DMonday_t + \beta_2 MonDST_t^{spring} + \beta_3 TueDST_t^{spring} \\
&+ \beta_4 WedDST_t^{spring} + \beta_5 ThurDST_t^{spring} + \beta_6 FriDST_t^{spring} \\
&+ \beta_7 MonDST_t^{autumn} + \beta_8 TueDST_t^{autumn} + \beta_9 WedDST_t^{autumn} \\
&+ \beta_{10} ThurDST_t^{autumn} + \beta_{11} FriDST_t^{autumn} + \sum_{i=1}^{p} \phi_i r_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t
\end{aligned} \tag{4.4}
$$

,where:

- β_0, $DMonday_t$, p,q,t are the same as in the previous specifications,
- $MonDST_t^{spring}$, $TueDST_t^{spring}$, $WedDST_t^{spring}$, $ThurDST_t^{spring}$, and $FriDST_t^{spring}$ are dummy variables that equal to 1 during the respective days of the first week after the spring transition,
- $MonDST_t^{autumn}$, $TueDST_t^{autumn}$, $WedDST_t^{autumn}$, $ThurDST_t^{autumn}$, and $FriDST_t^{autumn}$ are dummy variables that equal to 1 during specific days in the first week after autumn change.

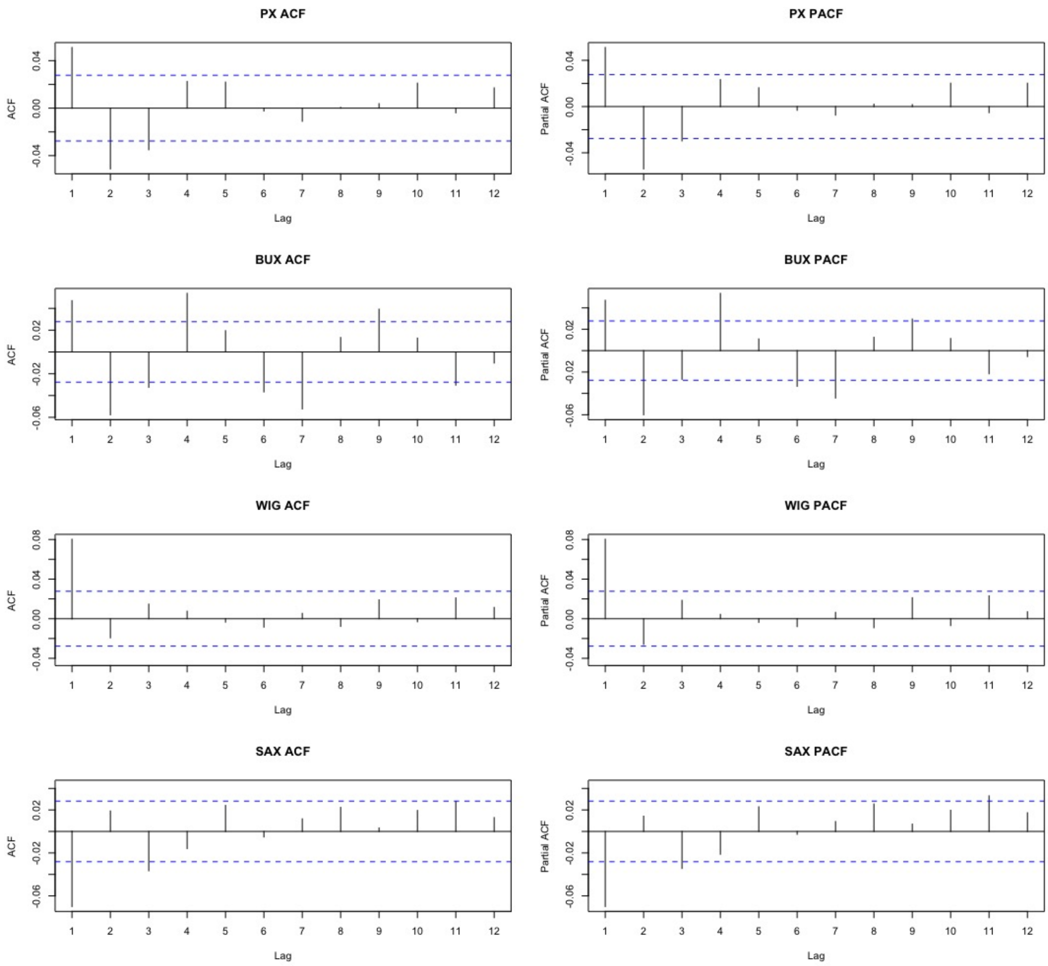
To conclude specifications in equations 4.1 and 4.2 capture the effect of the DST week. This effect might seem negligible when considering the week as a whole. Therefore, specifications 4.3 and 4.4 are used to account for potential intra-week differences following the change. On the other hand, the week breakdown introduces additional dummy variables, which might lead to overfitting of the model. Thus, to avoid both concerns, we also estimate equations 4.1 and 4.2 where the dummy variable DST will represent only Mondays following the transitions, as we expect Mondays to have the most pronounced effect in terms of magnitude and statistical significance.

ARIMA (p,d,q) order

To model the ARIMA process, we need to find the order of the autocorrelation process (p) and the moving average process (q) and the degree of differencing (d). Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) provide insight into AR and MA process orders. ACF shows the correlation between the dependent variable and its lagged values. On the other hand, PACF represents the partial correlation between the dependent variable and its lags, controlling for all shorter lags. Figure 4.1 depicts the ACF and

PACF for all four stocks. After performing ARIMA estimation with the lags indicated by the ACF and PACF, we found the magnitude, statistical significance and decided on the order of p and q based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC). As we are working with the returns, no further differencing is needed, and the degree is 0 for all four stocks. For the sake of parsimony and statistical significance, the following ARIMA orders were selected for the stock returns: PX - ARIMA(2,0,2), BUX - ARIMA (2,0,2), WIG - ARIMA (1,0,1) and SAX - ARIMA (1,0,1).

Figure 4.1: ACF and PACF of indexes BUX, PX, SAX, WIG



Note: Autocorrelation function and Partial autocorrelation function of returns of the indexes BUX, PX, SAX and WIG

4.1.2 Variance equation (GARCH)

Returns alone are only one half of the picture that financial economics study. Volatility analysis is important for empirical finance. From the introduction of the autoregressive conditional heteroskedasticity (ARCH) model (Engle 1982) the volatility forecasting has been evolving. Soon generalised autoregressive conditional heteroskedasticity (GARCH) by Bollerslev (1986) followed with multiple extensions such as exponential GARCH by Nelson (1991), the GJR model by Glosten *et al.* (1993), or the T-GARCH by Zakoian (1994).

To capture time varying volatility in the error term ϵ_t in equations 4.1, 4.2, 4.3 and 4.4 the GARCH(1,1) is used due to its parsimonity and effectiveness (see 5.2).

According to Bollerslev (1986) the GARCH(1,1) with be represented as:

$$\begin{aligned} \epsilon_t &\overset{\text{iid}}{\sim} N(0, \sigma_t^2) \\ \sigma_t^2 &= \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \end{aligned} \tag{4.5}$$

where, $N(0, \sigma_t^2)$ is the conditional distribution of ϵ_t with a zero mean and the variance σ_t^2. The conditional variance σ_t^2 is determined by the first lag of itself (σ_{t-1}^2) and the squares of past errors (ϵ_{t-1}^2).

4.1.3 ARIMAX(p,d,q)-GARCH(1,1)

Combining mean model specifications and equation 4.5, we have ARIMAX(p,d,q) - GARCH (1,1) model as follows:

$$\begin{aligned} r_t &= x_t \gamma + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \epsilon_t, \\ \sigma_t^2 &= \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \\ \epsilon_t &\overset{\text{iid}}{\sim} N(0, \sigma_t^2) \end{aligned} \tag{4.6}$$

where r_t are log-returns, x_t is $1xk$ vector of the controlling dummy variables specified based on equations 4.1, 4.2, 4.3, and 4.4; γ is the $kx1$ vector of the regression coefficients; ϕ_i and θ_j are the coefficient of AR(p) and MA(q) process, respectively. The rest of the variables and coefficients follows the specification in 4.5. To ensure positive conditional variance we assume that $\omega > 0$, $\alpha_1 \geq 0$,

$\beta \geq 0$. Moreover, to ensure stationarity, by having finite conditional variance, the assumption $\alpha + \beta < 1$ should hold.

4.2 Bayesian estimation

Maximum likelihood estimation (MLE) is considered a common technique for estimating ARIMA-GARCH-type models. On the one hand, MLE is straight forward, easy to perform, and asymptotically optimal if certain conditions hold (Bollerslev 1986). On the other hand, one has to deal with several difficulties when estimating ARIMA-GARCH-type models. Firstly, MLE's constraints imposed on the parameters to achieve positive and stationary conditional variance in maximisation of the likelihood function could lead to a convergence and optimisation failure. Secondly, in practice, we often assume the conditions for the optimal asymptotic properties of MLE estimators to hold. Moreover, the non-linearity of the GARCH-type models requires a large number of data for the asymptotic argument to hold (Ardia & Hoogerheide 1993). The last issue directly affects the estimation of our thesis. The Monday returns after the DST transition occur only twice a year. We have only 40 weeks (max 200 observations) possibly affected by the DST in a twenty-year time span for every index. Thus our estimated DST effect could suffer from small sample bias.

Bayesian approach has gained popularity due to several appealing advantages. With increasing computing power, it is becoming easier to employ. Moreover, it deals with the issues that were specified above. Firstly, proper priors specification allows any constraints to be incorporated. Secondly, using a suitable Markov chain Monte Carlo (MCMC) technique avoids convergence problems that can be encountered in MLE when local maxima occur. Thirdly, simulating from the joint posterior distribution provides us with precise distributions of the non-linear functions of the model parameters at a relatively low cost. Thus, Bayesian estimation allows for small sample analysis, probabilistic statements on non-linear functions of the model parameters, and robust estimation (Ardia & Hoogerheide 1993). The advantages mentioned above suggest promising results when performing the analysis using Bayesian estimation. Therefore this thesis employs Bayesian analysis as the primary estimation technique for our ARIMAX-GARCH model. To provide a robustness check, we also employ MLE.

Following closely Nakatsuma (2000), we have constructed the posterior density function for our model as follows:

$$p\left(\delta|Y,X\right)=\frac{\ell\left(Y|X,\delta\right)p(\delta)}{\int\ell\left(Y|X,\delta\right)p(\delta)d\delta}, \tag{4.7}$$

where $p(\delta)$ is the prior, δ is the set of all parameters in the ARIMAX(p,d,q)-GARCH(1,1) model, and $\ell(Y/X, delta)$ is the likelihood function. The likelihood function for our model is specified as:

$$\ell\left(Y|X,\delta\right)=\prod_{t=1}^{n}\frac{1}{\sqrt{2\pi\sigma_t^2}}\,exp\left[-\frac{\hat{\epsilon}_t^2}{2\sigma_t^2}\right] \tag{4.8}$$

where

$$\hat{\epsilon}_t=\begin{cases}\epsilon_0, & t=0\\ y_t-x_t\gamma-\sum_{i=1}^{p}\phi_j y_{t-j}-\sum_{j=1}^{q}\theta_j\hat{\epsilon}_{t-j}, & t=1,...,n\end{cases}$$

and this thesis treats assumes $y_0=\epsilon_0=0, y_t=0$ for $t<0$, and $x_t=0$ for $t\leq 0$ (Nakatsuma 2000).

Following Nakatsuma (2000); Ardia & Hoogerheide (2010), as the prior we use normal priors for ARIMAX parameters and truncated normal priors on the GARCH parameters:

$$\begin{aligned}p(\epsilon_0)&=N\left(\mu_{\epsilon_0},\Sigma_{\epsilon_0}\right)\\ p(\gamma)&=N\left(\mu_{\gamma},\Sigma_{\gamma}\right)\\ p(\phi)&=N\left(\mu_{\phi},\Sigma_{\phi}\right)\\ p(\theta)&=N\left(\mu_{\theta},\Sigma_{\theta}\right)\\ p(\omega)&=N\left(\mu_{\omega},\Sigma_{\omega}\right)I\left(\omega\in R_+\right)\\ p(\alpha)&=N\left(\mu_{\alpha},\Sigma_{\alpha}\right)I\left(\alpha\in R_+^0\right)\\ p(\beta)&=N\left(\mu_{\beta},\Sigma_{\beta}\right)I\left(\beta\in R_+^0\right)\end{aligned}$$

where, μ_* and Σ_* are hyperparameters; $I(*)$ is the indicator function which takes unity if the conditions in the bracket hold, otherwise zero; and $N\left(*\right)I\left(*\right)$ stands for truncated normal distribution.

Often, in Bayesian inference, the objective of the analysis is to obtain the expectation of a function of parameters:

$$E\left[f(\delta)\right] = \int f(\delta) p\left(\delta|Y, X\right) d\delta. \tag{4.9}$$

Analytical evaluation of formula 4.9 is difficult in our specification. Therefore, we need to apply a numerical integration technique, such as the Markov chain Monte Carlo method, with the selection of a proper algorithm. The next parts describe Markov chain Monte Carlo simulation, Metropolis-Hastings (MH) algorithm, and exact MCMC procedure of our estimation.

Markov chain Monte Carlo

Any simulation which generates many random values from a distribution is a Monte Carlo simulation. In a (first-order) Markov process, each state has no memory of the states before the present one, and a sequence of such states is called a Markov chain. Markov chain Monte Carlo simulations are mainly used to approximate multidimensional integrals (such as 4.9). The idea is to draw a set of samples $\{\delta^1, ..., \delta^N\}$ from a posterior density $p(\delta|Y, X)$, which is defined on a multidimensional space Δ. Then, if N is large enough, we can use the set of possible solutions of the system to approximate 4.9 such that:

$$E\left[f(\delta)\right] \approx \frac{1}{N} \sum_{i=1}^{N} f(\delta^i), \tag{4.10}$$

To generate the set of samples, we need to apply one of several sampling algorithms. In the case of our model, the conditional variance has a recursive nature. Thus, as Ardia & Hoogerheide (1993) point out, we do not know the joint posterior and the full conditional densities, regardless of the assumptions made on the scedastic function or the model disturbances. That is, there exists no associate prior such that the posterior distributions of the parameter fall within a known class (Ardia & Hoogerheide 1993). Therefore Metropolis-Hastings algorithm is used to generate the set of samples $\{\delta^{(i)}\}_{i=1}^{N}$.

Metropolis-Hastings algorithm

The Metropolis-Hastings (MH) algorithm is a specific type of a Monte Carlo process introduced by Metropolis *et al.* (1953) and later generalised by Hastings (1970). MH builds the Markov chain by sampling from a candidate density, where the proposed candidate draw is either accepted or rejected, based on an acceptance probability. If the proposed candidate is accepted, the chain shifts to the new value. If the proposed candidate is rejected, the shift does not occur, and the process again returns to the current value (Chib & Greenberg 1995). This paper employs a random walk MH variant where we generate draws conditional on the current value of the chain. The drawback of this variant is the correlation between draws which requires tuning of the proposal distribution and a high number of iterations to achieve robust results (Ardia & Hoogerheide 2010).

Following Nakatsuma (2000), in our model, we generate $\hat{\delta}$ from the proposal distribution $g(\delta)$, with the acceptance probability:

$$\lambda(\delta, \hat{\delta}) = min\left\{\frac{p(\hat{\delta}|Y, X)/g(\hat{\delta})}{p(\delta|Y, X)/g(\delta)}, 1\right\}. \tag{4.11}$$

MCMC procedure

Following Nakatsuma (2000) the outline of the MCMC procedure is:

1. generate δ_{ARMA} (given δ_{GARCH}),
2. generate δ_{GARCH} (given δ_{ARMA}),
3. apply MH algorithm,
4. repeat 1.-4. until the sequence becomes stable (see 4.2).

In step 1, δ_{GARCH} is obtained from the starting values for the first iteration. For the following iterations, δ_{GARCH} is obtained from the preceding iteration. In step 2, δ_{ARMA} is from step 1.

Convergence diagnostics

In MCMC theory, we can interpret the estimated coefficient once our chains converge to a stationary distribution. Thus, the achieved convergence is crucial for our analysis. Among the several methods which estimate whether the number of draws we simulate leads to a converged chain, we employed the Gelman Rubin diagnostic test.

Gelman Rubin diagnostic test requires us to generate $m \geq 2$ chains for each model. After the burn-in period, we calculate the within-chain and between-chain variance for every parameter according to the formulas below. (Gelman *et al.* 1992)

$$\begin{aligned} W =& \frac{1}{m}\sum_{j=1}^{m} s_j^2 \\ s_j^2 =& \frac{1}{n-1}\sum_{i=1}^{n}(\delta_{ij} - \bar{\delta_j})^2 \end{aligned} \tag{4.12}$$

$$\begin{aligned} B =& \frac{n}{m-1}\sum_{j=1}^{m}(\bar{\delta_j} - \tilde{\delta})^2 \\ \tilde{\delta} =& \frac{1}{m}\sum_{j=1}^{m}\bar{\delta_j} \end{aligned} \tag{4.13}$$

where W is the within-chain variance calculated as the mean of variances of each chain. B is between-chain variance, m is the number of generated chains, n is the number of iterations per chain.

Then, we weight sum of the within-chain and between-chain variance to obtain the estimated variance of the stationary distribution for each parameter as follows:

$$V\hat{a}r(\delta) = (1 - \frac{1}{n})W + \frac{1}{n}B \tag{4.14}$$

Lastly, we calculate a potential scale reduction factor:

$$\hat{R} = \sqrt{\frac{V\hat{a}r(\delta)}{W}} \tag{4.15}$$

where $\hat{R}$ is the potential scale reduction factor that indicates whether we should run more iterations to achieve convergence or not. If $\hat{R}$ is below 1.1 for every estimated parameter, we should have a chain that converged to a stationary distribution for each coefficient (Gelman *et al.* 1992).

4.2.1 Estimation process and tuning

Below we describe the estimation process. As the common estimation technique for ARIMA-GARCH models is Maximum Likelihood Estimation, there was a limited amount of R packages relevant for the Bayesian analysis. Therefore, we had to build the majority of the R functions to perform the Bayesian estimation ourselves. We tested the R functions on simulated ARIMAX-GARCH datasets where the true values were known. We were able to found coefficients close to the true values successfully for several different model specification and thus proceed to use the functions for real-world data.

For each of the four indexes, we have four different specifications of the DST effect on returns. Overall weekly DST effect, weekly DST effect divided into spring and autumn, overall daily DST effect, and daily DST effect divided into spring and autumn effect. Each specification requires simulating at least two chains to be able to test the convergence of the coefficients. We obtain every chain using 40000 iterations, where the number of iterations is big enough to assure convergence of all coefficients in all models, as presented in section 4.2. Simulating a total of 32 chains, each created using 40000 iterations, requires significant computing power. We used parallelisation to save time when performing the required amount of simulations. Preliminary tuning was required to achieve convergence and a desirable acceptance rate that properly explores the parameter space. The R source code used for the analysis are available upon request.

As Ardia & Hoogerheide (2010) pointed out, performing the Metropolis-Hastings algorithm in MCMC for ARMA-GARCH is not automatic and requires tuning to achieve the desired convergence, acceptance rate, and the proper exploration of the parameter space. We tuned the estimation by selecting: proper prior distribution of our parameter, the suitable standard deviation for our proposal function, and by identification of the burn-in period,

Firstly, we selected normal prior as mentioned in section 4.2. The hyperparameters' choice was such that the prior distribution is uninformative. This means that for the mean equation parameters, we chose normal priors with zero mean and large enough standard deviation, which equals two, to incorporate reasonable values of our parameters. For ω, α and β parameters, we chose truncated normal priors with a mean equal to 0.5 and standard error equal to 0.5, following our assumption from equation 4.5 ($\omega > 0$, $\alpha_1 \geq 0$, $\beta \geq 0$).

Secondly, we randomly drew the candidate values of the coefficient from the normal distribution, where the mean is the last accepted candidate value and the standard deviation is tuned to achieve the desired acceptance rate. The standard deviation for the proposal function is 0.02 for BUX, 0.015 for PX, 0.022 for SAX, 0.018 for WIG, such that there is an acceptance rate between 0.2-0.3.

Lastly, the burn-in period was estimated based on a trace plot. Intuitively, we identified the number of iteration after which the trace plot seems to stabilise (see α, β, ω coefficient in Figure A.5). The identification of the burn-in period is essential as the starting values can bias the results. Moreover, to be confident with our estimation, we performed the analysis with three different starting values to analyse whether the different starting values lead to different results. Firstly, we estimated all models that used zeros as starting values for all parameters except for ω (0.01) that has to be non-zero from our assumptions. Secondly, the MLE coefficients served as starting values. Lastly, the estimation started with the random numbers generated from the standard normal distribution for the mean equation N(0,1) and for the variance equation, we draw from the uniform distribution U(0.1,1). After the burn-in period, all three simulations lead to similar results. We believe that this supports the validity of our results as we achieved almost the same results using completely different starting points.

Chapter 5

Results and Discussion

This chapter summarises the estimation results based on models specified in Chapter 4. Firstly, we provide results and discussion of the DST effect on the stock market returns. Secondly, the robustness of our results is investigated.

5.1 Estimation results

In this section, we present the Bayesian estimation results of the daylight saving time effect on the stock market returns of the Visegrad Group countries. First, we show the weekly DST results with the respective discussion regarding the hypotheses' support, alignment with other literature, and differences and similarities between the indexes. Secondly, we present the breakdown of the weekly DST effect into specific daily effects. Again, the discussion incorporates hypotheses, the intuition behind the daily behaviour, and a comparison to the aggregate weekly results. The complete results for all indexes with the respective specification are disclosed in Table A.1 through A.16 in the Appendix.

5.1.1 DST effect of the first week

Table 5.1 summarises the estimation results of the effect of the DST on the stock market returns of the Visegrad Group in the week after the transition happens. The first column reports the overall DST effect. We can observe negative point estimates for the indexes BUX, PX, and WIG ranging from -0.186 to -0.101. We can interpret these results such that keeping all other factors fixed, the returns during the week following the DST are lower than other returns by approximately 10 to 18 basis points. Only the SAX point estimate is positive and close to zero. None of the coefficients is statistically significant. From the results, we find no support for Hypothesis 1. Similarly, Pinegar (2002), Müller *et al.* (2009), Berument *et al.* (2010), Gregory-Allen *et al.* (2010) find no statistical effect for other indexes around the world.

The other two columns in Table 5.1 provide the estimates of the DST effect following the spring and autumn transitions. Firstly, the spring daylight saving time estimates are negative in the first week following the DST transition for all investigated countries. This effect ranges from -0.255 to -0.015. However, none of the coefficients is statistically significant. Even though the direction of the point estimates is in line with Hypothesis 2, we do not have enough evidence to support it. Thus, the lack of statistical significance further supports the opponents of the DST effect.

Secondly, we can separate the autumn DST transition estimates into two groups. For BUX and WIG, we observe a negative effect in autumn, -0.219 and -0.123, respectively. Even though the autumn effect is negative, we can observe that the point estimates are lower compared to spring. Moreover, having both the spring and autumn effect negative is in line with the overall negative effect. For PX and SAX, there is a positive effect on the stock market returns following the autumn transition. The effect is around 0.04 and 0.05, respectively. Again, we can see the alignment with the overall effect, where for PX, the positive autumn estimates slightly offset the overall effect. In the case of SAX, the positive autumn estimate seems to prevail, leading to an overall positive effect. Nevertheless, we see that none of the coefficients is statistically different from zero. Thus, we do not have enough support for either Hypothesis 2 or Hypothesis 3. This finding is again in line with Pinegar (2002); Müller *et al.* (2009); Berument *et al.* (2010); Gregory-Allen *et al.* (2010).

5.1.2 Daily DST effect throughout the first week

Even though we did not find enough evidence to support the DST effect is statistically significant during the first week of the transition, we might argue that DST might affect only the closest day following the transition and for the remaining days, the effect is not significant and offsets the aggregate weekly effect. In this part, we present the results analysing this intra-week behaviour specified by equation 4.3 and equation 4.3. Figures 5.4,5.1, 5.2 and 5.3 visualize the effect of the DST on the stock market returns over the week following the time shift. We start with a brief description of the figures. A detailed description of the results alongside the discussion of the results follows. For all

Table 5.1: DST Effect of the first week after the time transition

Index	DST effect (%)	DST-Spring effect (%)	DST-Autumn effect (%)
PX	-0.101	-0.111	0.040
	(0.098)	(0.103)	(0.116)
BUX	-0.186	-0.255	-0.219
	(0.120)	(0.148)	(0.141)
WIG	-0.168	-0.211	-0.123
	(0.093)	(0.118)	(0.134)
SAX	0.019	-0.015	0.051
	(0.066)	(0.099)	(0.096)

Note: The table presents results about DST effect on stock market returns of Visegrad Group indexes during the first week following the spring, autumn and aggregate transition. The effect is not statistically significant. The point estimates and standard errors in parentheses are obtained using Bayesian estimation. Indexes: PX = Prague Stock Exchange Index, BUX = Budapest Stock Exchange Index, WIG - Warsaw Stock Exchange Index, SAX = Slovakian Stock Exchange Index

four indexes, we compare daily estimates with the weekly results in Table 5.1, discuss the intuition behind the depicted behaviour, and check the support of our hypotheses.

Each figure represents one stock market index. All figures consist of three graphs, with every graph representing one effect. The top graph visualises the overall effect of the DST for the given stock market returns. Bottom-left and bottom-right graph show the DST spring and autumn effect, respectively. The solid line represents point estimates in per cent. The 95% confidence interval surrounds the point estimates to showcase the precision of the estimated coefficient.

DST effect on PX

Let us start with Prague Stock Index results in Figure 5.1. The breakdown of DST's spring effect on PX starts with the Monday following the transition having a negative point estimate (-0.22). Then Monday DST effect is followed by Tuesday (0.01), Wednesday (-0.14), and Thursday (0.13), fluctuating around zero. The most considerable negative effect occurs on Friday (-0.36). None of the DST spring estimates is statistically significant.

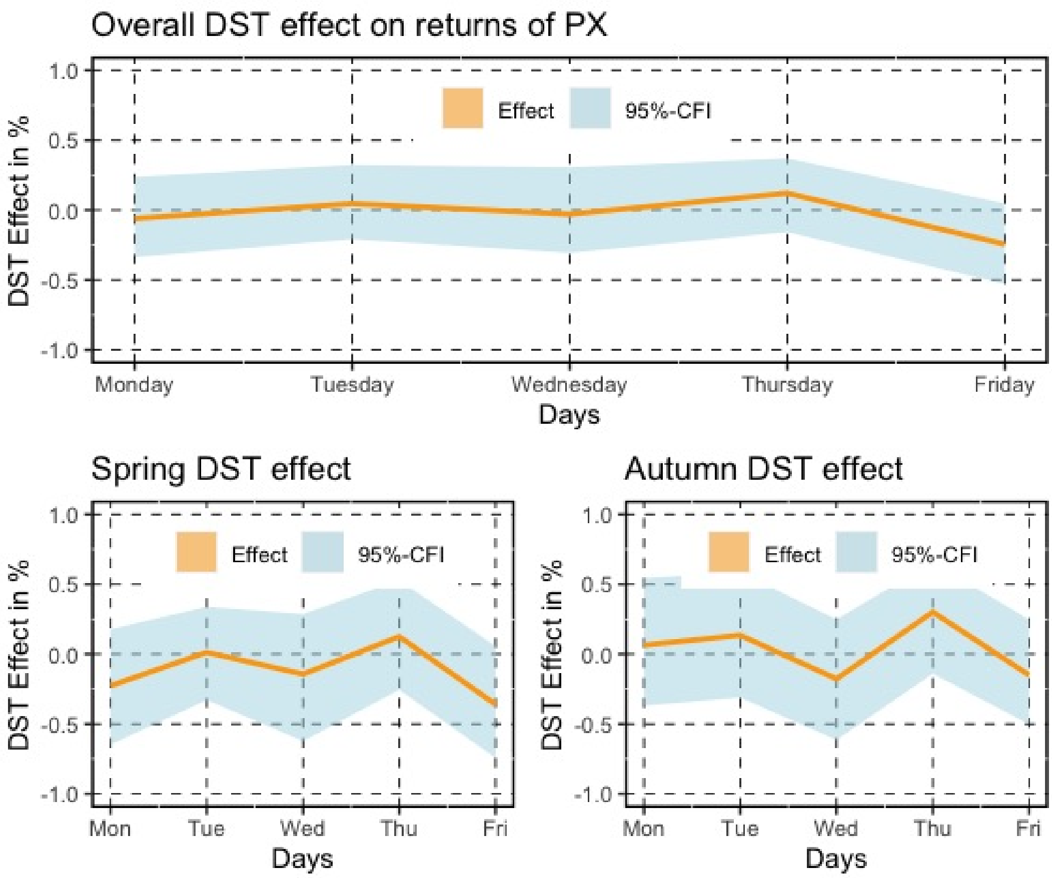
For the autumn effect, only Monday and Tuesday estimates are 0.06 and

0.14, respectively. The effect then fluctuates with negative values on Wednesday (-0.18) to positive values on Thursday (0.30) back to Friday's (-0.15) negative values. Again, none of the estimates is statistically different from zero.

Regarding the overall DST effect, none of the variables is statistically significant. The coefficients are as follows: Monday (-0.06), Tuesday (0.05), Wednesday (-0.03), Thursday (0.12), Friday (-0.25). We observe a very similar pattern for the spring effect, indicating that the spring effect dominates the autumn effect. The only magnitude is different as the spring is offset by autumn.

To conclude the support of hypotheses on the daylight saving time effect on the Prague Stock Index returns. Firstly, we do not find enough evidence to support either Hypothesis 4 or Hypothesis 5.

Figure 5.1: Breakdown of the DST effect on the returns of PX



Note: The overall, spring, and autumn daily effects of the DST throughout the first week for the returns of PX. The point estimates are obtained using Bayesian estimation and 95% confidence intervals are calculated based on the standard errors from the same estimation.

DST effect on SAX

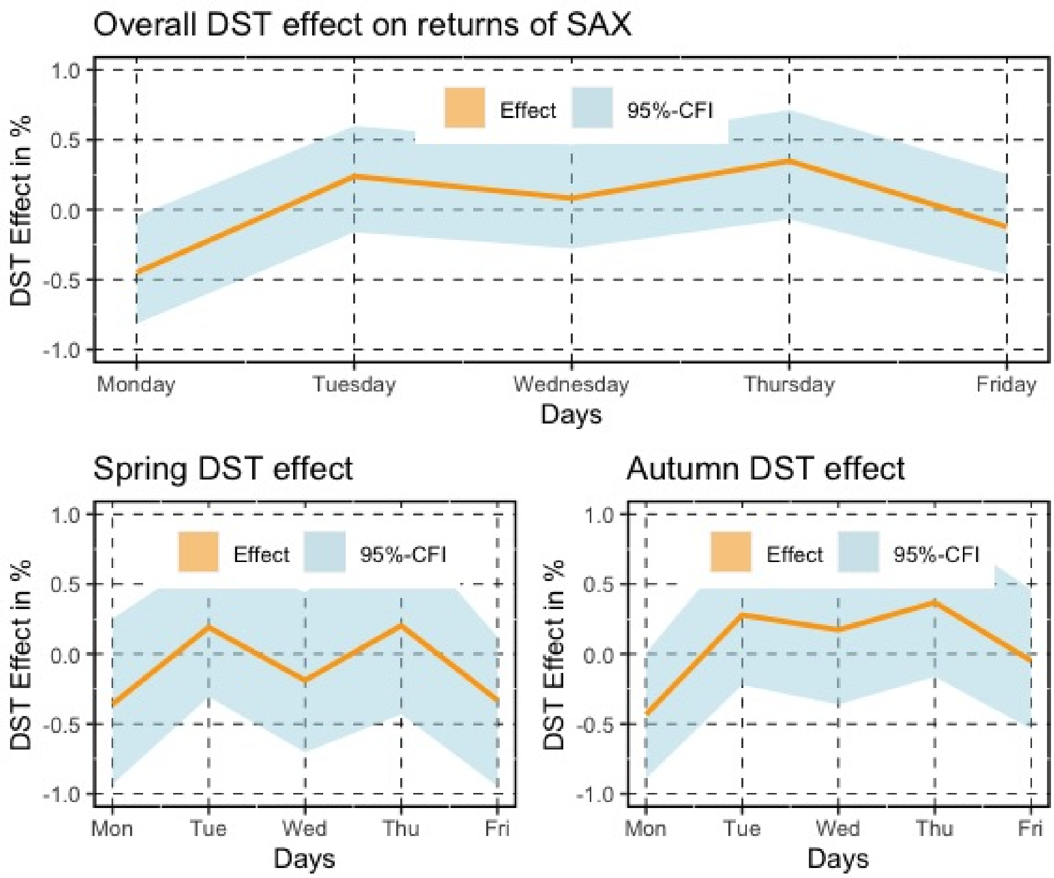
Secondly, we focus on the DST effect on SAX returns in Figure 5.2. The Monday DST effect indicates a decrease in returns in spring, with a point estimate being -0.36. Then, the DST effect fluctuates around zero with point estimates equal to 0.20 on Tuesday, -0.19 on Wednesday, 0.20 on Thursday, and -0.33 on Friday. None of the estimates is statistically significant.

For the autumn, the DST effect on Monday is negative (-0.43), which is followed by positive point estimates on Tuesday (0.28), Wednesday (0.17), and Thursday (0.37). The Friday DST effect (-0.05) is negative and very close to zero. The confidence intervals again showcase that none of the estimated effects is statistically significant.

The overall effect resembles the combination of the spring and autumn effect. We observe the significant negative coefficient of the Monday DST effect (-0.45). Thus, we might interpret this result such that keeping all other factors fixed, the SAX stock market returns on Mondays following the DST time shifts are lower than other SAX stock market returns by approximately 45 basis points. Other days of the week have insignificant statistical coefficients, and the pattern resembles the autumn transition. The estimated coefficients for the rest of the week are 0.23 for Tuesday, 0.08 for Wednesday, 0.35 for Thursday, and -0.12 for Friday.

Overall we can derive several conclusions from the DST effect on the SAX returns. Firstly, DST has the highest impact on Monday following the shift. We even find a statistically significant coefficient for the overall effect. This change in the significance is due to two factors. The first one being the negative Monday DST coefficient for both spring and autumn. The second one is the increase in the sample size as we combined twenty observations in spring and twenty observations in autumn into forty observations overall. Therefore, we find support for Hypothesis 4 in the case of the overall DST effect on SAX. Moreover, we find support for Hypothesis 5 as the overall coefficients for the rest of the week are not statistically different from zero. Lastly, we have to remember that SAX is a very illiquid index, and changes in prices do not occur daily, thus potentially creating a bias in our estimation.

Figure 5.2: Breakdown of the DST effect on the returns of SAX



Note: The overall, spring, and autumn daily effects of the DST throughout the first week for the returns of SAX. The point estimates are obtained using Bayesian estimation and 95% confidence intervals are calculated based on the standard errors from the same estimation.

DST effect on WIG

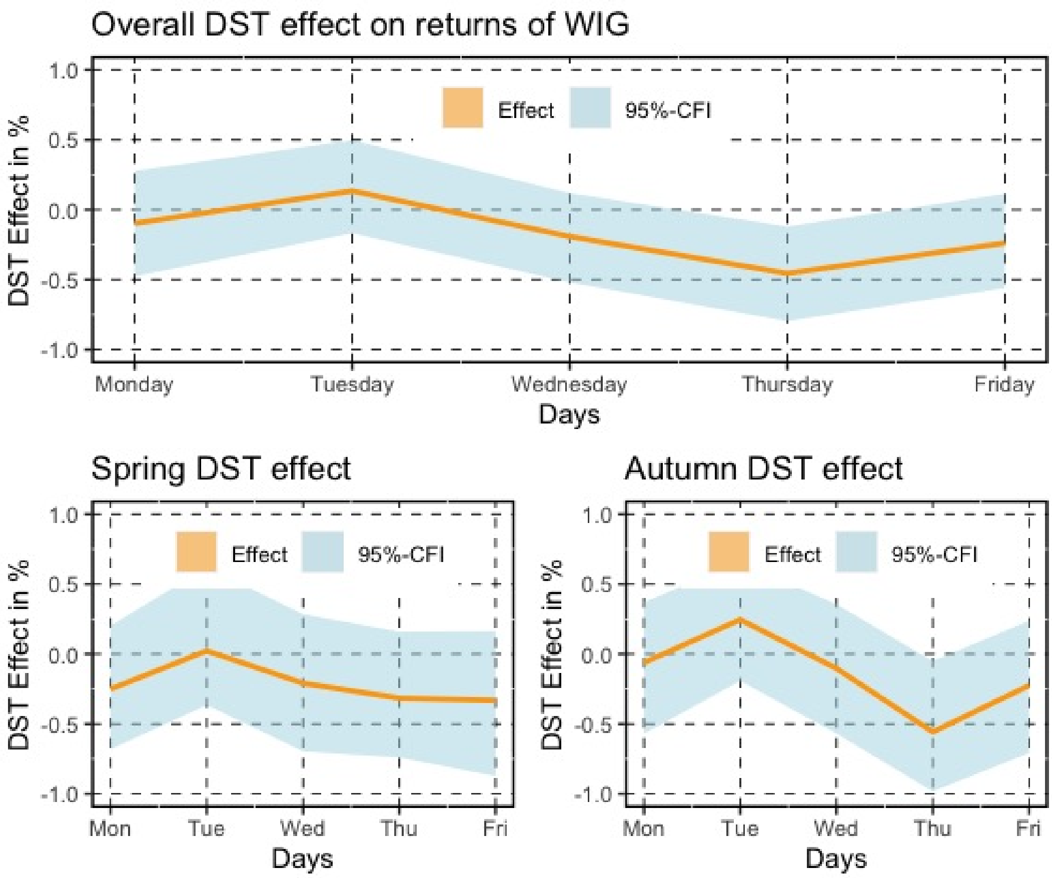
We continue with the DST effect on the WIG returns in Figure 5.3. In spring, We have most of the estimated coefficients negative, starting with the DST effect on Monday amounting to -0.25. The only exception is on Tuesday after the change, where the effect is 0.02. Following Tuesday, it seems that the negative effect is slightly increasing throughout the week - Wednesday (-0.21), Thursday (-0.32), Friday (-0.33). Every point estimate is not statistically different from zero.

The autumn DST effect follows a slightly different pattern compared to spring. The negative DST effect on Monday is smaller (-0.06). On the other hand, the Tuesday DST effect is higher (0.25). The effect for the rest of the week is negative with different magnitudes compared to spring - Wednesday (-0.10), Thursday (-0.55), Friday (-0.23). Even though the Thursday DST effect is the only statistically significant coefficient, we do not find any rationale behind it and proceed to attribute the significance to a mere chance.

The overall effect naturally results from the combination of the spring and autumn DST effect. Thus, the results resemble the similarities of both transitions. We observe DST's negative effects for all days except Tuesday (0.13), with the minimum occurring on Thursday (-0.45). The Monday, Wednesday and Friday DST estimates are -0.10, -0.19 and -0.24, respectively. Again, none of the estimated coefficients is statistically significant.

We can summarise the results of the DST effect on WIG as follows. The point estimates indicate that both spring and autumn transition seem to affect WIG returns negatively. The results do not provide enough evidence to support either Hypothesis 4 or Hypothesis 5.

Figure 5.3: Breakdown of the DST effect on the returns of WIG



Note: The overall, spring, and autumn daily effects of the DST throughout the first week for the returns of WIG. The point estimates are obtained using Bayesian estimation and 95% confidence intervals are calculated based on the standard errors from the same estimation.

DST effect on BUX

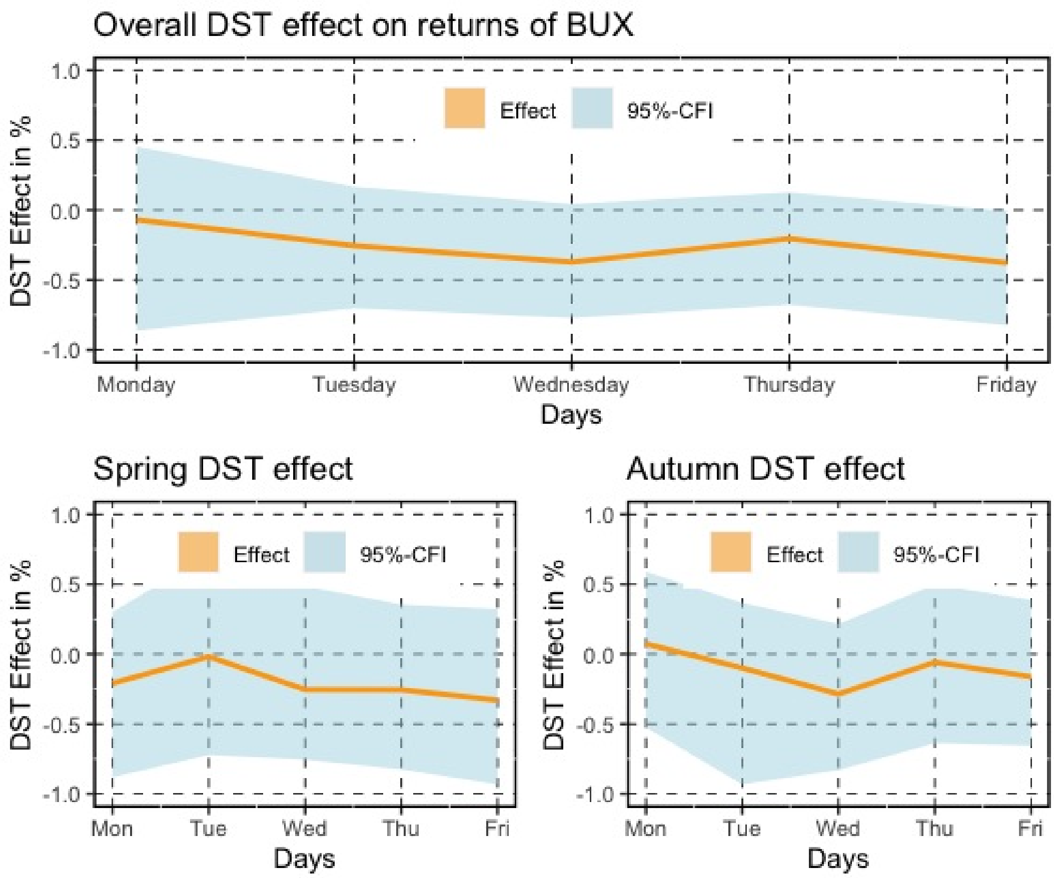
Lastly, we present the results of the DSG effect on BUX returns. Figure 5.4illustrate our findings. In spring, we observe negative DST effect estimates for all days - Monday (-0.20), Tuesday (-0.02), Wednesday (-0.25), Thursday (-0.25), Friday (-0.33). Again, none of the estimates is significantly different from zero.

The autumn DST effect starts with Monday having a positive point estimate (0.07). The effect throughout the rest of the week is negative - Tuesday (-0.10), Wednesday (-0.28), Thursday (-0.06), Friday (-0.16). Again, none of the estimated coefficients is statistically significant.

The overall DST effect is negative for all days following the week after the DST transition - Monday (-0.07), Tuesday (-0.25), Wednesday (-0.37), Thursday (-0.20), Friday (-0.38). The only statistically significant DST effect occurs on Friday, which we again attribute to a chance in a small sample.

To conclude BUX results, we might point out that the DST has a negative effect on both spring and autumn transition for almost all days in the weeks following the transition. However, there is not enough evidence to support either Hypothesis 4 or Hypothesis 5.

Figure 5.4: Breakdown of the DST effect on the returns of BUX



Note: The overall, spring, and autumn daily effects of the DST throughout the first week for the returns of BUX. The point estimates are obtained using Bayesian estimation and 95% confidence intervals are calculated based on the standard errors from the same estimation.

5.2 Robustness checks

In this section, we provide several robustness checks to our results. The robustness checks are comparison with MLE estimation, other GARCH specifications, and outliers effect. The validity of our results was investigated by the residual analysis and converge results.

5.2.1 Maximum likelihood estimation comparison

Even though we believe that the Bayesian approach is a valid estimation technique, below there is a comparison with the MLE estimates as one of the robustness checks. Table 5.2 present only the comparison between the DST coefficient for the weekly effect. We can draw several conclusions based on the table below. On the one hand, we can see that each coefficient's sign is the same for both estimations. On the other hand, we can see that the two approaches differ in magnitude. For almost all variables, we can see that the Bayesian analysis yields higher coefficients than MLE. Furthermore, from all the models in section A.1 in Appendix A, we can observe that log-likelihood is bigger for Bayesian analysis. We could argue that the Bayesian estimation may perform better than MLE in the case of small sample estimation in terms of likelihood. Other than that, the two approaches seem to yield very similar results.

Table 5.2: Comparison between Bayesian estimation and MLE

Index	Overall DST (%)		DST-Spring (%)		DST-Autumn (%)	
	Bayes	MLE	Bayes	MLE	Bayes	MLE
PX	−0.101	−0.050	−0.111	−0.080	0.040	0.001
	(0.098)	(0.064)	(0.103)	(0.086)	(0.116)	(0.096)
BUX	−0.186	−0.056	−0.255	−0.089	−0.219	−0.018
	(0.120)	(0.091)	(0.148)	(0.124)	(0.141)	(0.131)
WIG	−0.168	−0.109	−0.211	−0.114	−0.123	−0.104
	(0.093)	(0.077)	(0.118)	(0.105)	(0.134)	(0.113)
SAX	0.019	0.003	−0.015	−0.089	0.051	0.085
	(0.066)	(0.074)	(0.099)	(0.106)	(0.096)	(0.101)

Note: The table compares the point estimates and standard errors (in parentheses) between the Bayesian estimation and maximum likelihood estimation of the overall, spring, and autumn DST effect on stock market returns of the Visegrad Group indexes in the first week following the time shift.

Other GARCH specifications

One could argue that GARCH(1,1) does not capture the behaviour of the conditional volatility enough. We found that for SAX, based on the sign bias test, there is a possibility of the leverage effect. The leverage effect is a phenomenon often found in the financial literature where the negative returns' impact has a different magnitude on the volatility compared to the positive returns' impact. The E-GARCH model could capture the possible leverage effect. However, our work's focus is to find the effect of the DST in the mean equation. We performed the analysis for other specifications, but we did not find the differences in our interest's estimated coefficient (DST effect) to vary significantly. Thus, to keep the estimation as simple as possible, we have decided to keep GARCH(1,1) as the primary estimation technique, as the GARCH(1,1) is efficient enough for our analysis.

5.2.2 Outliers

As Pinegar (2002) pointed out, the several extreme values occurring during the weeks following the change could be misinterpreted as the DST effect on the returns. To tackle this problem, we perform the following robustness check. From the Figure 3.2 we can observe several extreme values from 2000 to 2020 for all indexes. Intuitively, the highest extreme values occur during the 2008 Financial Crisis and the subsequent sovereign debt crisis, which hit Europe in 2013. Nevertheless, there are some other extreme values throughout the estimated period. Naturally, there is a question of how to deal with these extreme values. We dedicate this subsection to the identification of the outliers and their impact on our estimation.

Starting with the identification, we detect outliers using the standard process of inter-quantile range. All relevant information regarding the identified outliers for all indexes is in the Table 5.3. There is a total number of identified outliers, the number of outliers occurring during DST transition week, and the exact days the DST outliers occur to discuss their potential impact on our estimation. We can see that there are only a few extreme values during our 'DST affected' period.

Table 5.3: Outliers analysis

	Outliers	DST week outliers	Dates (days)
BUX	212	0	-
PX	254	1	2000-03-29 (Wed)
SAX	650	1	2000-03-31 (Fri)
WIG	230	2	2000-03-29 (Wed), 2000-03-30 (Thur)

Note: The table presents the number of extreme values in the data and their occurrence in the DST affected weeks for Visegrad Group stock indexes.

The second and most important part is the treatment of outliers. On the one hand, we do not want the results to be biased due to several extreme values. On the other hand, since only a few extreme values occurred during the first week following the spring and autumn transition, we expect not to have a significant bias in the estimated coefficient. Therefore, as a robustness check, we first perform the analysis without all identified outliers. We find no significant difference in the estimated coefficient without the presence of the outliers. All the coefficient weekly coefficient remained the same in terms of magnitude and statistical significance. The point estimates and standard errors differed only marginally. Nonetheless, there was one difference in the residual analysis. We achieved the normality of the standardised residuals when we disregarded the outliers. We might, however, lose some information by simply disregarding the extreme values.

As we want to preserve as much information as possible in our estimation, we do not want to discard all these extreme values. Therefore we opt for only the first and ninety-ninth percentiles. Thus, we have excluded the most extreme values that affected the normality of our residuals. The final number of outliers excluded is 11 for BUX, 13 for PX, 11 for SAX, and 13 for WIG, which is only around 0.005% relative to the total number of observation. Moreover, none of these outliers occurs during the first week following the DST transition and most of them occurred during the Financial Crisis.

5.2.3 Residual analysis

To capture the dependencies in the volatility, we performed ARIMA-GARCH estimation. As our initial assumption was that $\epsilon_t \in N(0, \sigma_t)$, we normalized our residuals based on the estimated σ_t. Table A.19 and Figure A.1-A.4 in Appendix presents the results of the normalised residuals analysis. We provide these results only for the weekly effect models, as other specifications yield almost identical statistics.

Firstly, the sign bias test and weighted Ljung-Box test analyse the presence of further dependencies in squared standardised residuals. For the majority of the models, we find no further dependencies in the normalised residuals if GARCH is used. For SAX, there is possibly a leverage effect due to the sign bias tests. E-GARCH could capture this behaviour. We elaborate on this in section 5.2.1, where we perform robustness checks using other GARCH specifications.

Secondly, the Jarque-Bera test on standardised residuals indicates whether the standardised residuals follow the standard normal distribution. We might observe that the residuals are not entirely normal. However, in section 5.2.2 we identify that several extreme values drive the non-normal behaviour.

5.2.4 Convergence results

From the MCMC theory, we want to achieve the convergence of our chains to the stationary target distribution. Following the section 4.2, we evaluated the convergence using the Gelman Rubin diagnostic test for every variable coefficient in all our models and their specifications (Gelman *et al.* 1992). We achieved convergence for every parameter after 40 000 draws for each model estimating weekly effects of the DST. For illustration, in Table 5.4, we present the convergence results for the parameters of the model of weekly DST effect on the returns of all indexes as the weekly specification has the least amount of variables. Each parameter achieved convergence since $\hat{R}$ is less than 1.1 for all the coefficients.

Furthermore, we employ a visual inspection of the convergence using the trace plot for each variable's coefficient. The idea behind the trace plot is to see how is our simulation moving around the parameter space. We disclose the plots for the WIG weekly DST effect on the returns in Appendix Figure A.6 and Figure A.5. The former depicts the trace plot for the whole simulated chain. The latter is the trace plot of the chain after the burn-in period of 4000 iterations. We see that, especially for the variance model coefficients, the simulation converged after around one thousand observations.

Table 5.4: Gelman-Rubin Diagnostics

	BUX	PX	WIG	SAX
μ	1	1	1	1.03
AR_1	1	1	1.02	1.01
AR_2	1	1	-	-
MA_1	1.03	1.02	1	1.01
MA_2	1.03	1.09	-	-
MondayEffect	1.05	1.09	1.01	1.01
Weekly DST effect	1.01	1.04	1	1.03
ω	1	1	1.02	1.01
α_1	1	1	1.01	1.01
β_1	1	1.01	1.01	1.01

Note: The results of the Gelman-Rubin diagnostics test. We report a potential scale reduction factor $\hat{R}$, which indicates convergence if below 1.1.

Chapter 6

Conclusion

Following seminal works of Kamstra *et al.* (2000) and Berument *et al.* (2010), we examine the presence of market anomaly, caused by the DST policy, in the relatively illiquid stock markets indexes of the Visegrad Group. The study aims to add to the existing literature regarding the market anomalies and DST policy effects on the markets that other researchers have not examined yet.

Furthermore, this study employs a Bayesian approach to the ARIMAX-GARCH models, which broadens the existing literature concerning the application of the Bayesian estimation in the financial analysis. We tested four specifications to capture the heterogeneity between the DST spring and autumn transitions and the adaptation to these transitions. The first specification analyses the aggregate weekly DST effect for each index. The second specification aims to capture the difference in the weekly DST effects in spring and autumn. The third specification examines the DST effect differences among the days within the week following the transition. The last specification investigates spring and autumn differences in daily DST effects analysed in the third specification.

Our findings contribute to the literature as follows. We do not find any statistically significant effect of the DST on the returns of the Visegrad Group stock markets. Even though the direction of the point estimates is negative during the spring transition for all indexes, the effects are not big nor statistically significant. These findings are in line with Pinegar (2002); Müller *et al.* (2009); Berument *et al.* (2010); Gregory-Allen *et al.* (2010). Lastly, the Bayesian approach, as a rather novel estimation technique in terms of ARIMA-GARCH models, yields very similar results to the MLE in terms of the DST effect. Therefore, we argue that DST market anomaly is not present among the Visegrad Group stock markets. Moreover, our findings add value to the ongoing discussion about market anomalies and the efficient market hypotheses. Mounting discussion regarding the relevancy of the daylight saving time policy has led European Commission to cancellation of the mandatory unified DST policy as of 2021. If any country decides to abandon the DST policy, we would be presented with a unique opportunity for further research in all areas of the DST influence.

The findings suffer from the two limitations. The first being the small sample size, with only forty transitions within our investigated period. Although we employed Bayesian estimation to tackle this problem, despite the potential structural changes in the market, obtaining the data for a more extensive period is one way to increase the results' precision. Secondly, the lack of an explicit control group might lead to a bias in our estimation. The solution for this problem might be in the future when the DST policy is cancelled.

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Appendix A

Results: Complementary Tables

A.1 Estimation Results

Table A.1: DST effect on BUX in the first week following the shift

	MLE	Bayes
mu	-0.06^{**}	-0.06^{**}
	(0.02)	(0.02)
ar1	0.18^{**}	0.23^{***}
	(0.06)	(0.02)
ar2	-0.89^{***}	-0.53^{***}
	(0.06)	(0.02)
ma1	-0.17^{*}	-0.24^{***}
	(0.07)	(0.03)
ma2	0.87^{***}	0.55^{***}
	(0.06)	(0.06)
Monday effect	−0.02	−0.11
	(0.04)	(0.10)
Weekly DST effect	−0.06	−0.19
	(0.09)	(0.12)
omega	0.03^{***}	0.06^{***}
	(0.01)	(0.00)
alpha1	0.09^{***}	0.10^{***}
	(0.01)	(0.01)
beta1	0.90^{***}	0.86^{***}
	(0.01)	(0.01)
Log likelihood	−8300.61	−8307

Note: Results for BUX of the ARIMA-GARCH with mean model specification 4.1 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.2: DST effect on BUX in the first week following the shift divided into spring and autumn effect

	MLE	Bayes
mu	-0.04^{**}	-0.08^{***}
	(0.01)	(0.00)
ar1	0.16^{***}	0.23^{***}
	(0.00)	(0.04)
ar2	-0.98^{***}	-0.53^{***}
	(0.00)	(0.05)
ma1	-0.16^{***}	-0.21^{***}
	(0.00)	(0.04)
ma2	0.98^{***}	0.50^{***}
	(0.00)	(0.05)
Monday Effect	-0.04	-0.04^{***}
	(0.03)	(0.00)
Spring weekly DST effect	-0.08	-0.26
	(0.09)	(0.15)
Autumn weekly DST effect	0.00	-0.22
	(0.10)	(0.14)
omega	0.02^{***}	0.06^{***}
	(0.00)	(0.00)
alpha1	0.14^{***}	0.11^{***}
	(0.01)	(0.01)
beta1	0.85^{***}	0.86^{***}
	(0.01)	(0.01)
Log likelihood	-7371.64	-8302

Note: Results for BUX of the ARIMA-GARCH with mean model specification 4.2 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.3: Daily DST effect on BUX in the first week following the shift

	MLE	Bayes
mu	-0.06^{**}	-0.08^{***}
	(0.02)	(0.02)
ar1	0.18^{**}	0.21^{**}
	(0.06)	(0.07)
ar2	-0.89^{***}	-0.44^{***}
	(0.05)	(0.04)
ma1	-0.17^{*}	-0.19^{*}
	(0.07)	(0.07)
ma2	0.87^{***}	0.40^{***}
	(0.06)	(0.04)
Monday Effect	-0.03	-0.04^{***}
	(0.04)	(0.00)
Mon DST Effect	0.29	-0.07
	(0.21)	(0.33)
Tue DST Effect	-0.14	-0.25
	(0.20)	(0.23)
Wed DST Effect	-0.11	-0.37
	(0.19)	(0.20)
Thur DST Effect	-0.30	-0.20
	(0.20)	(0.19)
Fri DST Effect	0.00	-0.38^{*}
	(0.22)	(0.20)
omega	0.03^{***}	0.06^{***}
	(0.01)	(0.01)
alpha1	0.09^{***}	0.10^{***}
	(0.01)	(0.01)
beta1	0.90^{***}	0.86^{***}
	(0.01)	(0.01)
Log likelihood	-8298.40	-8301

Note: Results for BUX of the ARIMA-GARCH with mean model specification 4.3 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.4: Daily DST effect on BUX in the first week following the shift divided into spring and autumn effect

	MLE	Bayes
mu	-0.06^{**}	-0.08^{***}
	(0.02)	(0.00)
ar1	0.18^{**}	0.17^{***}
	(0.06)	(0.04)
ar2	-0.89^{***}	-0.41^{***}
	(0.05)	(0.03)
ma1	-0.16^{*}	-0.16^{***}
	(0.07)	(0.04)
ma2	0.87^{***}	0.38^{***}
	(0.06)	(0.04)
Monday Effect	−0.03	-0.04^{***}
	(0.04)	(0.00)
Spring Mon DST Effect	0.39	−0.20
	(0.29)	(0.28)
Spring Tue DST Effect	−0.28	−0.02
	(0.28)	(0.40)
Spring Wed DST Effect	−0.17	−0.25
	(0.27)	(0.31)
Spring Thur DST Effect	−0.23	−0.25
	(0.28)	(0.29)
Spring Fri DST Effect	−0.14	−0.33
	(0.28)	(0.30)
Autumn Mon DST Effect	0.19	0.07
	(0.29)	(0.28)
Autumn Tue DST Effect	−0.00	−0.10
	(0.28)	(0.31)
Autumn Wed DST Effect	−0.05	−0.28
	(0.27)	(0.26)
Autumn Thur DST Effect	−0.38	−0.06
	(0.29)	(0.27)
Autumn Fri DST Effect	0.23	−0.16
	(0.34)	(0.26)
omega	0.03^{***}	0.06^{***}
	(0.01)	(0.01)
alpha1	0.09^{***}	0.11^{***}
	(0.01)	(0.00)
beta1	0.90^{***}	0.86^{***}
	(0.01)	(0.00)
Log likelihood	−8297.52	−8302

Note: Results for BUX of the ARIMA-GARCH with mean model specification 4.4 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.5: DST effect on PX in the first week following the shift

	MLE	Bayes
mu	-0.04^{**}	-0.05^{**}
	(0.01)	(0.01)
ar1	1.60^{***}	0.07^{***}
	(0.01)	(0.00)
ar2	-0.96^{***}	-0.40^{***}
	(0.01)	(0.00)
ma1	-1.60^{***}	0.09^{***}
	(0.01)	(0.13)
ma2	0.95^{***}	0.39^{***}
	(0.01)	(0.04)
Monday Effect	−0.04	−0.03
	(0.03)	(0.07)
Weekly DST effect	−0.05	−0.10
	(0.06)	(0.98)
omega	0.02^{***}	0.05^{***}
	(0.00)	(0.00)
alpha1	0.14^{***}	0.16^{***}
	(0.01)	(0.01)
beta1	0.86^{***}	0.81^{***}
	(0.01)	(0.01)
Log likelihood	−7373.95	−7390

Note: Results for PX of the ARIMA-GARCH with mean model specification 4.1 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.6: DST effect on PX in the first week following the shift divided into spring and autumn effect

	MLE	Bayes
mu	-0.04^{**}	-0.08^{***}
	(0.01)	(0.01)
ar1	0.16^{***}	-0.06
	(0.00)	(0.04)
ar2	-0.98^{***}	-0.39^{***}
	(0.00)	(0.07)
ma1	-0.16^{***}	0.09^{*}
	(0.00)	(0.04)
ma2	0.98^{***}	0.38^{***}
	(0.00)	(0.07)
Monday	-0.04	$0-07^{***}$
	(0.03)	(0.00)
Spring Weekly DST effect	-0.08	-0.11
	(0.09)	(0.103)
Autumn Weekly DST effect	0.00	0.04
	(0.10)	(0.116)
omega	0.02^{***}	0.05^{***}
	(0.00)	(0.00)
alpha1	0.14^{***}	0.16^{***}
	(0.01)	(0.00)
beta1	0.85^{***}	0.81^{***}
	(0.01)	(0.00)
Log likelihood	-7371.64	-7386

Note: Results for PX of the ARIMA-GARCH with mean model specification 4.2 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.7: Daily DST effect on PX in the first week following the shift

	MLE	Bayes
mu	-0.04^{**}	-0.07^{***}
	(0.01)	(0.01)
ar1	0.17^{***}	0.7
	(0.00)	(0.07)
ar2	-0.98^{***}	-0.18^{***}
	(0.00)	(0.04)
ma1	-0.16^{***}	−0.05
	(0.00)	(0.07
ma2	0.98^{***}	0.17^{***}
	(0.00)	(0.04)
Monday Effect	−0.04	0.08^{***}
	(0.03)	(0.01)
Mon DST Effect	−0.06	−0.06
	(0.15)	(0.14)
Tue DST Effect	−0.15	0.05
	(0.14)	(0.12)
Wed DST Effect	−0.08	−0.03
	(0.15)	(0.16)
Thur DST Effect	−0.04	0.12
	(0.14)	(0.14
Fri DST Effect	0.12	−0.25
	(0.14)	(0.15)
omega	0.02^{***}	0.05^{***}
	(0.00)	(0.00)
alpha1	0.14^{***}	0.16^{***}
	(0.01)	(0.00)
beta1	0.85^{***}	0.81^{***}
	(0.01)	(0.00)
Log likelihood	−7370.82	−7385

Note: Results for PX of the ARIMA-GARCH with mean model specification 4.3 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.8: Daily DST effect on PX in the first week following the shift divided into spring and autumn effect

	MLE	Bayes
mu	-0.04^{**}	-0.07^{***}
	(0.01)	(0.00)
ar1	0.17^{***}	-0.06
	(0.00)	(0.05)
ar2	-0.98^{***}	-0.21^{***}
	(0.00)	(0.02)
ma1	-0.16^{***}	0.04
	(0.00)	(0.05)
ma2	0.98^{***}	0.20^{***}
	(0.00)	(0.02)
Monday Effect	-0.04	0.08^{***}
	(0.03)	(0.00)
Spring Mon DST Effect	-0.11	-0.22
	(0.20)	(0.19)
Spring Tue DST Effect	-0.20	0.01
	(0.19)	(0.17)
Spring Wed DST Effect	-0.07	-0.14
	(0.19)	(0.23)
Spring Thur DST Effect	-0.04	0.13
	(0.18)	(0.20)
Spring Fri DST Effect	0.06	-0.36
	(0.22)	(0.20)
Autumn Mon DST Effect	0.00	0.06
	(0.22)	(0.22)
Autumn Tue DST Effect	-0.08	0.14
	(0.21)	(0.23)
Autumn Wed DST Effect	-0.10	-0.18
	(0.23)	(0.22)
Autumn Thur DST Effect	-0.04	0.30
	(0.21)	(0.21)
Autumn Fri DST Effect	0.18	-0.15
	(0.19)	(0.19)
omega	0.02^{***}	0.05^{***}
	(0.00)	(0.00)
alpha1	0.14^{***}	0.16^{***}
	(0.01)	(0.00)
beta1	0.85^{***}	0.81^{***}
	(0.01)	(0.00)
Log likelihood	-7370.57	-7384

Note: Results for PX of the ARIMA-GARCH with mean model specification 4.4 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.9: DST effect on WIG in the first week following the shift

	MLE	Bayes
mu	-0.03	-0.06^{***}
	(0.02)	(0.02)
ar1	-0.22	-0.26^{***}
	(0.19)	(0.02)
ma1	0.30	0.33^{***}
	(0.18)	(0.02)
Monday Effect	-0.07	0.05^{***}
	(0.03)	(0.01)
Weekly DST Effect	-11	-0.17
	(0.08)	(0.09)
omega	0.02^{***}	0.04^{***}
	(0.00)	(0.00)
alpha1	0.07^{***}	0.09^{***}
	(0.01)	(0.01)
beta1	0.92^{***}	0.88^{***}
	(0.01)	(0.01)
Log likelihood	-7507	-7548

Note: Results for WIG of the ARIMA-GARCH with mean model specification 4.1 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.10: DST effect on WIG in the first week following the shift divided into spring and autumn effect

	MLE	Bayes
mu	-0.03	-0.06^{***}
	(0.02)	(0.00)
ar1	-0.22	-0.31^{***}
	(0.19)	(0.02)
ma1	0.29	0.38^{***}
	(0.18)	(0.02)
Monday Effect	-0.07	0.05^{***}
	(0.03)	(0.00)
Spring weekly DST effect	-0.11	-0.21
	(0.11)	(0.12)
Autumn weekly DST effect	-0.10	-0.12^{***}
	(0.11)	(0.13)
omega	0.02^{***}	0.04^{***}
	(0.00)	(0.00)
alpha1	0.07^{***}	0.09^{***}
	(0.01)	(0.00)
beta1	0.92^{***}	0.88^{***}
	(0.01)	(0.00)
Log likelihood	-7505.11	-7545

Note: Results for WIG of the ARIMA-GARCH with mean model specification 4.2 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.11: Daily DST effect on WIG in the first week following the shift

	MLE	Bayes
mu	−0.03	-0.06^{***}
	(0.02)	(0.00)
ar1	−0.21	-0.24^{***}
	(0.19)	(0.02)
ma1	0.28	0.31^{***}
	(0.18)	(0.02)
Monday Effect	−0.06	0.05
	(0.03)	(0.03)
Mon DST Effect	−0.20	−0.10
	(0.17)	(0.20)
Tue DST Effect	−0.28	0.13
	(0.16)	(0.17)
Wed DST Effect	0.16	−0.19
	(0.16)	(0.17)
Thur DST Effect	−0.02	−0.45
	(0.16)	(0.17)
Fri DST Effect	−0.20	−0.24
	(0.17)	(0.16)
omega	0.02^{***}	0.04^{***}
	(0.00)	(0.00)
alpha1	0.07^{***}	0.09^{***}
	(0.01)	(0.01)
beta1	0.92^{***}	0.88^{***}
	(0.01)	(0.01)
Log likelihood	−7502.65	−7545

Note: Results for WIG of the ARIMA-GARCH with mean model specification 4.3 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.12: Daily DST effect on WIG in the first week following the shift divided into spring and autumn effect

	MLE	Bayes
mu	-0.03	-0.05^{***}
	(0.02)	(0.00)
ar1	-0.21	-0.20^{***}
	(0.19)	(0.02)
ma1	0.28	0.27^{***}
	(0.18)	(0.02)
Monday Effect	-0.06	0.05^{***}
	(0.03)	(0.00)
Spring Mon DST Effect	-0.10	-0.25
	(0.25)	(0.23)
Spring Tue DST Effect	-0.20	0.02
	(0.22)	(0.25)
Spring Wed DST Effect	0.05	-0.21
	(0.22)	(0.24)
Spring Thur DST Effect	-0.15	-0.32
	(0.22)	(0.23)
Spring Fri DST Effect	-0.18	-0.33
	(0.24)	(0.28)
Autumn Mon DST Effect	-0.29	-0.06
	(0.24)	(0.23)
Autumn Tue DST Effect	-0.37	0.25
	(0.23)	(0.21)
Autumn Wed DST Effect	0.28	-0.10
	(0.23)	(0.24)
Autumn Thur DST Effect	0.13	-0.55^{*}
	(0.24)	(0.24)
Autumn Fri DST Effect	-0.22	-0.23
	(0.24)	(0.25)
omega	0.02^{***}	0.04^{***}
	(0.00)	(0.00)
alpha1	0.07^{***}	0.09^{***}
	(0.01)	(0.00)
beta1	0.92^{***}	0.88^{***}
	(0.01)	(0.00)
Log likelihood	-7501.77	-7556

Note: Results for WIG of the ARIMA-GARCH with mean model specification 4.4 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.13: DST effect on SAX in the first week following the shift

	MLE	Bayes
mu	-0.03	-0.02^{***}
	(0.02)	(0.00)
ar1	0.23	0.14^{***}
	(0.20)	(0.03)
ma1	-0.34	-0.24^{***}
	(0.20)	(0.04)
Monday Effect	0.02	0.03^{***}
	(0.04)	(0.00)
Weekly DST effect	0.00	0.02
	(0.07)	(0.07)
omega	0.01^{***}	0.02^{***}
	(0.00)	(0.00)
alpha1	0.03^{***}	0.03^{***}
	(0.00)	(0.00)
beta1	0.97^{***}	0.95^{***}
	(0.00)	(0.00)
Log likelihood	-7409.73	-7412

Note: Results for SAX of the ARIMA-GARCH with mean model specification 4.1 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.14: DST effect on SAX in the first week following the shift divided into spring and autumn effect

	MLE	Bayes
mu	-0.03	-0.02^{***}
	(0.02)	(0.00)
ar1	0.24	0.16^{***}
	(0.20)	(0.02)
ma1	-0.34	-0.27^{***}
	(0.19)	(0.02)
Monday Effect	0.02	0.03^{***}
	(0.04)	(0.00)
Spring Weekly DST effect	-0.09	-0.02
	(0.11)	(0.10)
Autumn Weekly DST effect	0.08	0.05
	(0.10)	(0.10)
omega	0.01^{***}	0.02^{***}
	(0.00)	(0.00)
alpha1	0.03^{***}	0.03^{***}
	(0.00)	(0.00)
beta1	0.97^{***}	0.95^{***}
	(0.00)	(0.00)
Log likelihood	-7409.02	-7412

Note: Results for SAX of the ARIMA-GARCH with mean model specification 4.2 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.15: Daily DST effect on SAX in the first week following the shift

	MLE	Bayes
mu	-0.03^{*}	-0.03^{***}
	(0.02)	(0.00)
ar1	0.22	0.17^{***}
	(0.22)	(0.02)
ma1	-0.32	-0.28^{***}
	(0.21)	(0.02)
Monday Effect	0.03	0.05^{***}
	(0.04)	(0.00)
Mon DST Effect	-0.15	-0.45^{*}
	(0.18)	(0.20)
Tue DST Effect	-0.39^{*}	0.23
	(0.18)	(0.19)
Wed DST Effect	0.17	0.08
	(0.18)	(0.20)
Thur DST Effect	0.17	0.35
	(0.19)	(0.20)
Fri DST Effect	0.23	-0.12
	(0.18)	(0.19)
omega	0.01^{***}	0.01^{***}
	(0.00)	(0.00)
alpha1	0.03^{***}	0.04^{***}
	(0.00)	(0.00)
beta1	0.97^{***}	0.95^{***}
	(0.00)	(0.00)
Log likelihood	-7405.28	-7408

Note: Results for SAX of the ARIMA-GARCH with mean model specification 4.3 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Table A.16: Daily DST effect on SAX in the first week following the shift divided into spring and autumn effect

	MLE	Bayes
mu	-0.03^{*}	-0.02^{***}
	(0.02)	(0.00
ar1	0.24	0.25^{***}
	(0.21)	(0.02)
ma1	−0.34	-0.35^{***}
	(0.20)	(0.02)
Monday Effect	0.03	0.05^{***}
	(0.04)	(0.00)
Spring Mon DST Effect	-0.70^{*}	−0.36
	(0.27)	(0.30)
Spring Tue DST Effect	−0.16	0.20
	(0.26)	(0.25)
Spring Wed DST Effect	0.22	−0.19
	(0.26)	(0.30)
Spring Thur DST Effect	−0.08	0.20
	(0.26)	(0.32)
Spring Fri DST Effect	0.05	−0.33
	(0.27)	(0.27)
Autumn Mon DST Effect	0.22	−0.43
	(0.23)	(0.23)
Autumn Tue DST Effect	-0.57^{*}	0.28
	(0.24)	(0.26)
Autumn Wed DST Effect	0.13	0.17
	(0.24)	(0.28)
Autumn Thur DST Effect	0.43	0.37
	(0.27)	(0.28)
Autumn Fri DST Effect	0.27	−0.05
	(0.24)	(025)
omega	0.01^{***}	0.02^{***}
	(0.00)	(0.00)
alpha1	0.03^{***}	0.04^{***}
	(0.00)	(0.00)
beta1	0.97^{***}	0.94^{***}
	(0.00)	(0.00)
Log likelihood	−7400.56	−7408

Note: Results for SAX of the ARIMA-GARCH with mean model specification 4.4 and both Bayesian and MLE estimation. Standard errors are in parentheses and $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

A.2 Preliminary Analysis Results

Figure A.1: Visualisation of the residuals' normality for BUX

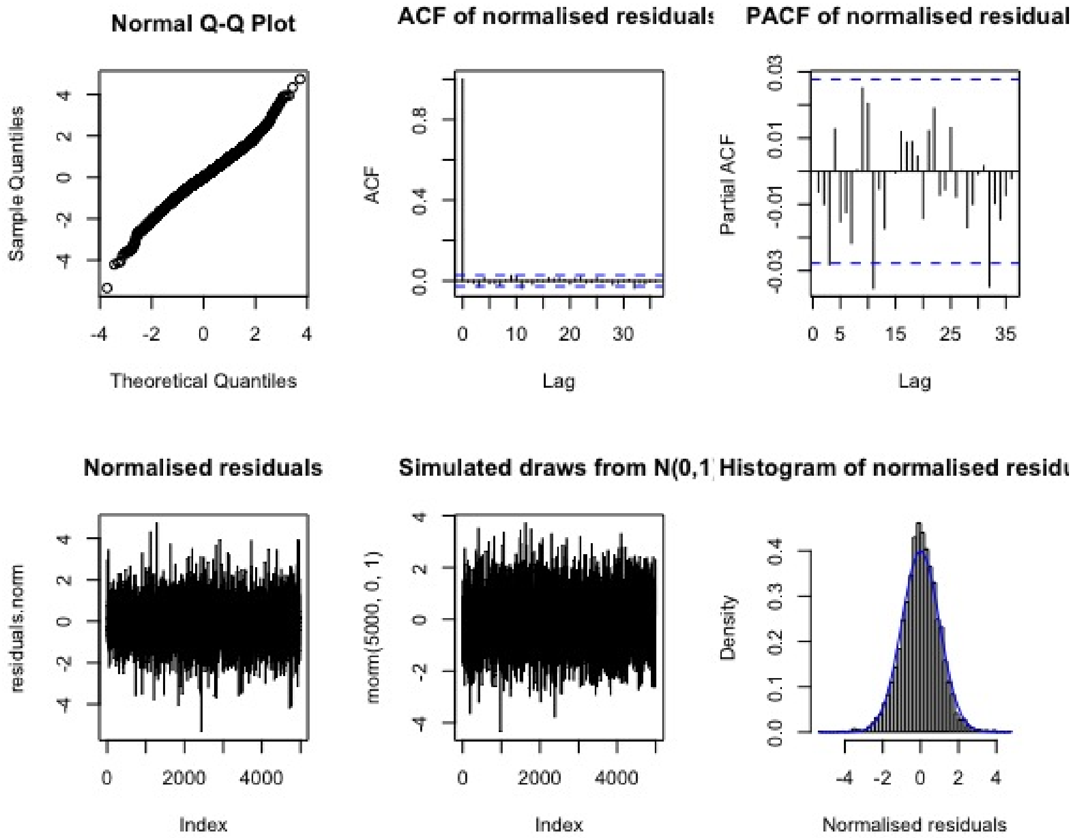

Figure A.2: Visualisation of the residuals' normality for PX

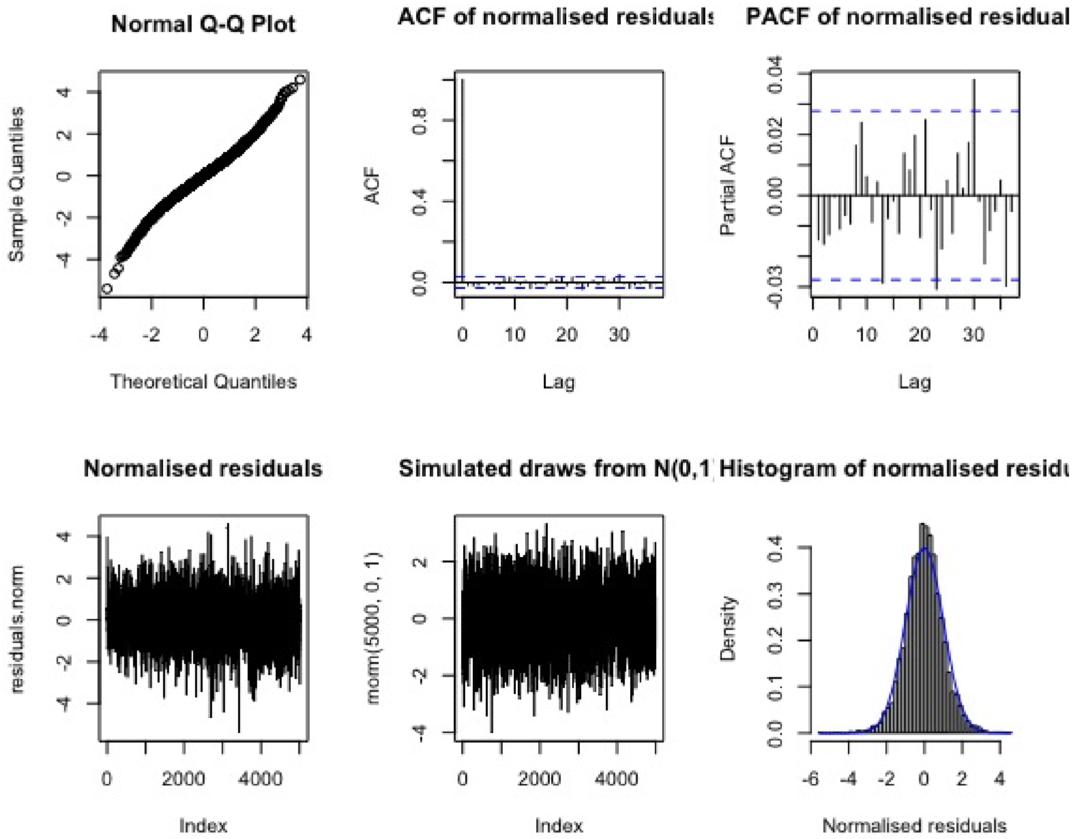

Figure A.3: Visualisation of the residuals' normality for SAX

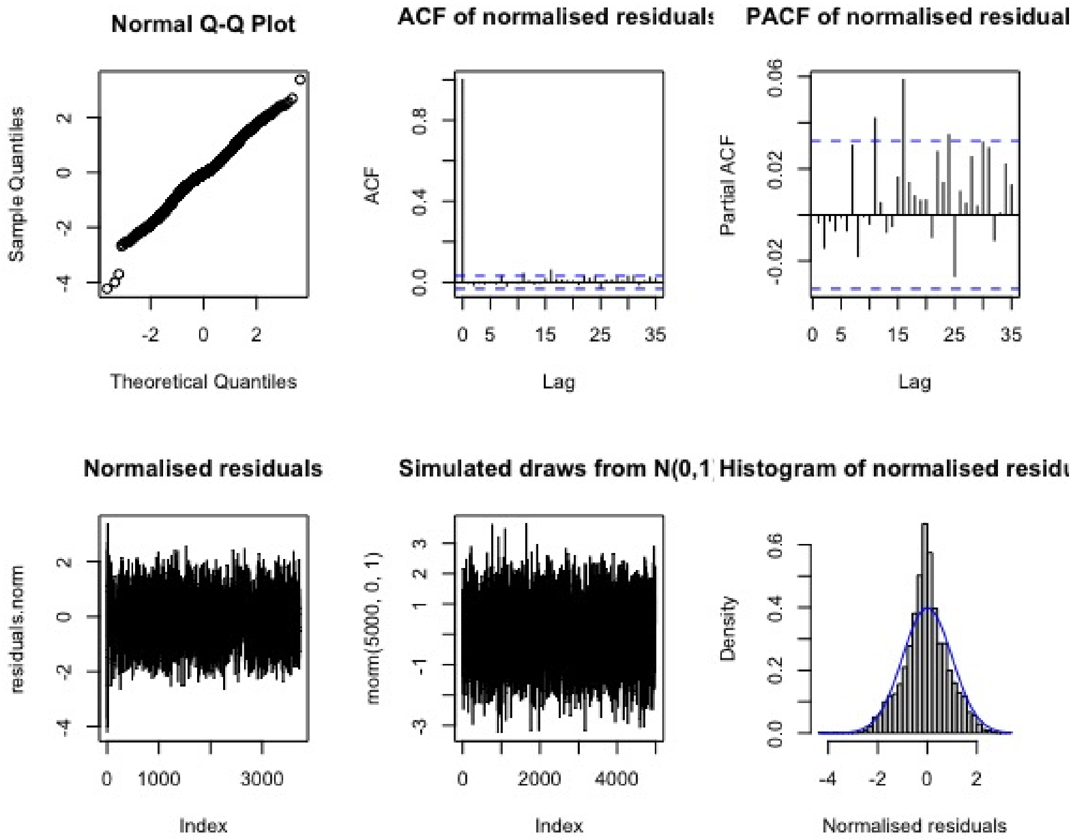

Figure A.4: Visualisation of the residuals' normality for WIG

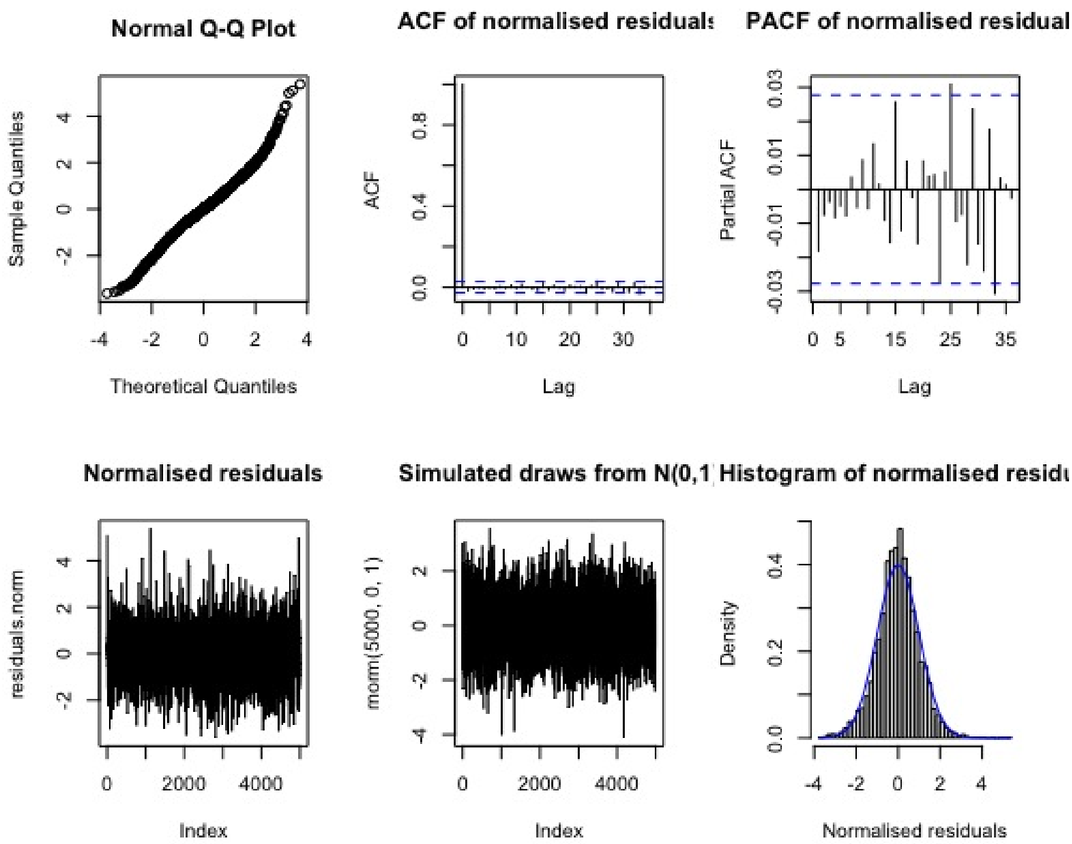

Table A.17: Augmented Dickey-Fuller test of the closing prices of the indexes in the Visegrad Group

	BUX	PX	SAX	WIG
No drift & no trend				
Lag = 1	0.02	0.40	0.40	0.24
Lag = 3	0.01	0.39	0.39	0.19
Lag = 5	0.01	0.39	0.37	0.19
With drift & no trend				
Lag = 1	0.31	0.64	0.91	0.74
Lag = 3	0.26	0.65	0.91	0.71
Lag = 5	0.19	0.64	0.92	0.67
With drift & with trend				
Lag = 1	0.53	0.82	0.97	0.50
Lag = 3	0.50	0.83	0.97	0.49
Lag = 5	0.45	0.84	0.98	0.50

Figure A.5: Traceplot of chain for DST weekly effect on WIG

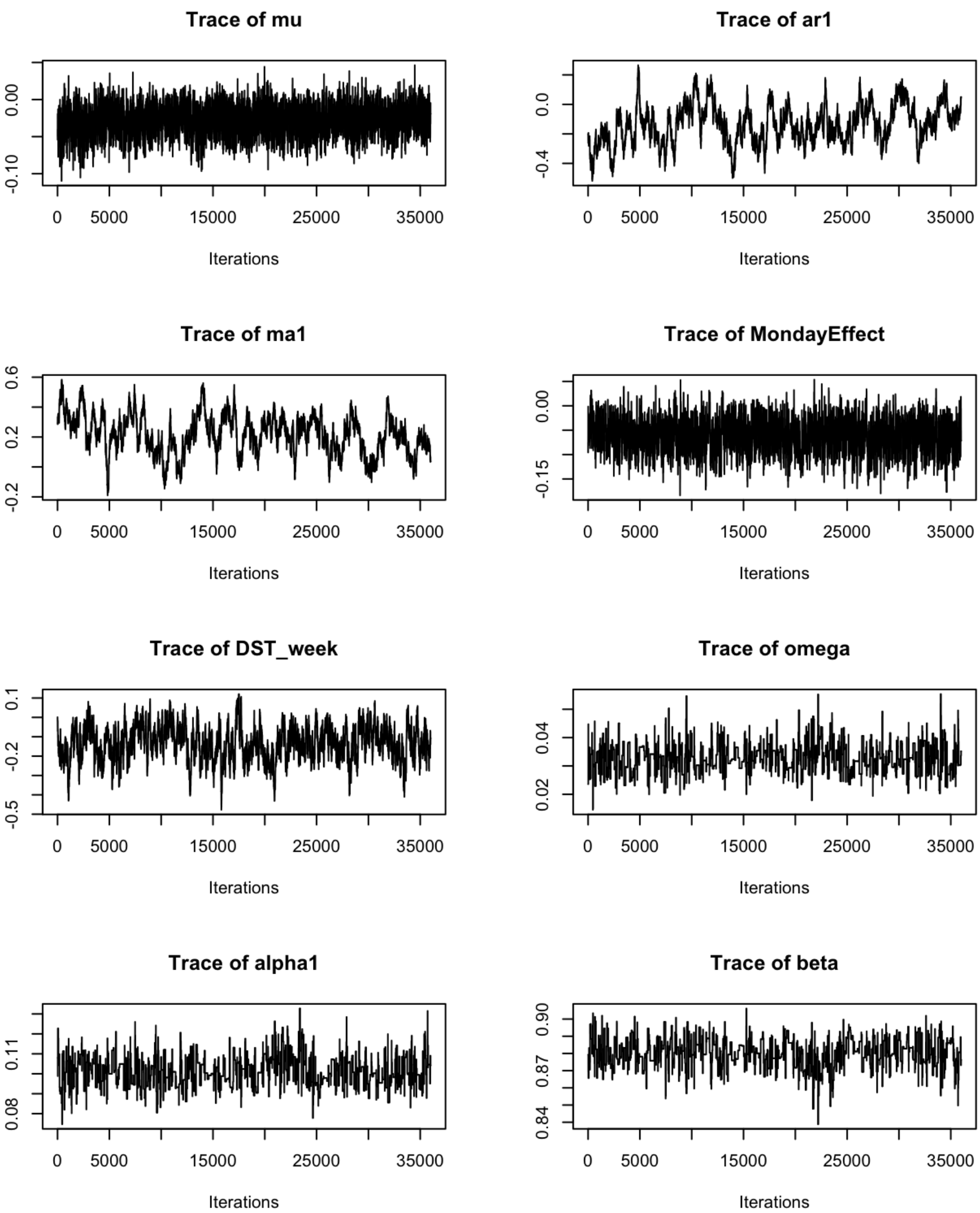

Figure A.6: Traceplot of chain for DST weekly effect on WIG including burnin period

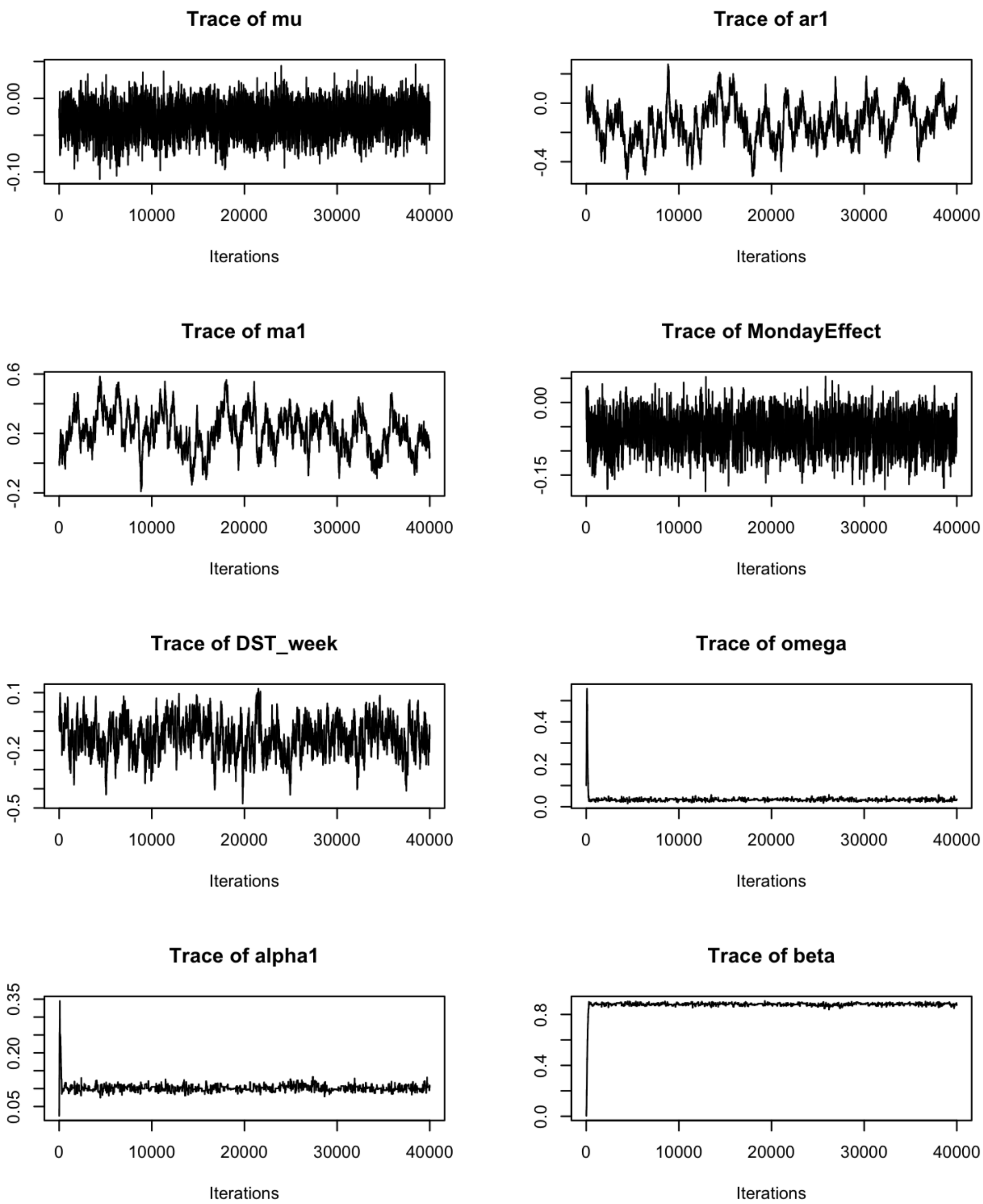

Table A.18: Statistical test on the residuals from the ARIMAX(p,l,q) model.

	BUX	PX	SAX	WIG
Augmented Dickey Fuller (up to 10 lags)	0.010	0.010	0.010	0.010
Jarque-Bera	0	0	0	0
ARCH-LM p-value	0	0	0	0
Ljung-Box	0	0	0	0

Table A.19: Statistical test on the standardized residuals from the ARIMAX(p,l,q)-GARCH(1,1) model.

	BUX	PX	SAX	WIG
Sign Bias significance	-	-	$*$	-
Weighted Ljung-Box (p-value)	0.67	0.52	0.48	0.2
Jarque-Bera (p-value)	0.3	0.1	0.1	0.1