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The Impact of Domestic Political News on Prague Stock Exchange in the Years 2022 and 2023: A Study on Market Activity and Price Dynamics

Bachelor's thesis

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Abstract

This thesis investigates the impact of domestic political news on the Prague Stock Exchange, focusing on the Prime Market segment. By employing both panel data and dynamic panel data models, we examine the influence of political news on stock price volatility. Our findings reveal that political news significantly impacts price changes during trading hours, while non-trading hours remain unimpacted. We also observe strong autocorrelation in price changes. No significant day-of-week effect on price changes during trading hours was found. However, non-trading hours show distinct price change patterns on Tuesdays and Fridays. These results offer valuable insights for investors and policymakers, highlighting the role of political news in market dynamics.

JEL Classification	C33, G12, G14, H79,
Keywords	volatility, stock exchange, dynamic panel data, domestic political news
Title	The Impact of Domestic Political News on Prague Stock Exchange in the Years 2022 and 2023: A Study on Market Activity and Price Dynamics

Abstrakt

Tato práce zkoumá vliv domácích politických zpráv na Pražskou burzu se zaměřením na segment Prime Market. S využitím panelových i dynamických panelových datových modelů zkoumáme vliv politických zpráv na volatilitu cen akcií. Naše zjištění ukazují, že politické zprávy významně ovlivňují změny cen během obchodních hodin, zatímco na neobchodní hodiny vliv nemají. Pozorujeme také silnou autokorelaci cenových změn. Nebyl zjištěn žádný významný vliv dne v týdnu na změny cen během obchodních hodin. V neobchodních hodinách se však v úterý a v pátek projevují výrazné cenové změny. Tyto výsledky nabízejí cenné poznatky pro investory i pro politiky a zdůrazňují roli politických zpráv na dynamiku trhu.

Klasifikace JEL	C33, G12, G14, H79,
Klíčová slova	volatilita, burza, dynamická panelová data, domácí politické zprávy
Název práce	Dopad domácích politických zpráv na Pražskou burzu v letech 2022 a 2023: Studie tržní aktivity a cenové dynamiky

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Acronyms and Abbreviations

ADF	Augmented Dickey-Fuller test
BLUE	Best linear unbiased estimator
Colt	Colt CZ Group
ČEZ	Skupina ČEZ
ČTK	Česká Tisková Kancelář
Erste	Erste Group Bank
FEM	Fixed effects model
GMM	Generalized method of moments
JSE	Johannesburg Stock Exchange
KB	Komerční banka
Kofola	Kofola ČeskoSlovensko
Moneta	MONETA Money Bank
PSE	Prague Stock Exchange
REM	Random effects model
VIF	Variance inflation factors
VIG	Vienna Insurance Company

Chapter 1

Introduction

The Prague Stock Exchange (PSE) plays a pivotal role in the Czech economy, functioning as a crucial platform for domestic companies seeking capital. By accessing financial resources through the PSE, Czech companies can secure the funding needed for growth and development, ensuring that wealth remains within the country. This, in turn, can potentially foster a more prosperous economic environment for the Czech Republic. Therefore, it is essential for investors and policymakers to understand the factors that influence stock prices on the PSE. Given that the PSE is a relatively small market, we have focused our analysis on the most visible segment of the PSE, namely the Prime Market. (It should be noted that the PSE is divided into several markets. The Prime Market is the designated venue for trading blue-chip stocks.)

Recently, domestic political news has notably influenced stock prices at the PSE. For example, on the 27th of June, 2022, the market capitalization of ČEZ experienced a significant decline of CZK 70 billion in response to discussions surrounding potential tax changes, and on the 18th of May, 2023, by CZK 49 billion following proposals to modify the laws governing publicly traded companies. These instances underscore the potential impact of political news on market fluctuations. This thesis aims to clarify the precise effects of domestic political news on stock market fluctuations, thereby providing valuable insights for investors and policymakers.

This study's primary research question is: "Does political news influence the price volatility at the PSE more than generic, uncategorized news?" The objective is to determine whether political news has a more significant impact on stock prices than all other published news. This investigation is grounded in the hypothesis that political news is a substantial factor in stock price changes. Additionally, this study explores the differences between open-to-close and close-to-open price changes and how news impacts both price volatilities.

Previous studies have highlighted the influence of news on stock markets in various contexts. For instance, van der Merwe & vd M. Smit (1997) examined this phenomenon at the Johannesburg Stock Exchange (JSE) and concluded that political news significantly affects market activity. They found that "volatilities of the All Share and Industrial Indices are more sensitive to the classification (content) of news items and correlate better with the subcategories of Political and Domestic Political news events, than with the All News category." (van der Merwe & vd M. Smit, 1997, p. 21). French & Roll (1986) found that the close-to-open price variance is considerably smaller than the open-to-close price volatility, suggesting that the lower speed of flow of the information during non-trading hours plays a crucial role in explaining lower close-to-open price variance.

This study employs both panel data and dynamic panel data methodologies to test the cross-sectional impacts of news on the market as a whole rather than on indices or specific shares. The dynamic panel data approach is particularly relevant, given that smaller financial markets, such as the PSE, tend to exhibit high levels of autocorrelation, as established in the literature review. Additionally, while there is some correlation between various markets, the PSE is more likely to be influenced by domestic events and global developments.

Our analysis demonstrates a notable divergence in the magnitude and slopes of lagged price changes between the close-to-open and open-to-close hours. In addition, the open-to-close hours are more susceptible to the influence of past price fluctuations. Furthermore, our findings indicate that the volume of news classified as political news is more effective than the overall daily news flow in predicting price volatility, which aligns with the findings of van der Merwe & vd M. Smit (1997).

The principal limitation of our analysis is the use of inconsistent and biased estimators due to the presence of endogenous variables. Consequently, all the results must be subjected to rigorous evaluation, and any conclusions drawn from them should be subjected to further scrutiny.

The structure of this thesis is as follows: Chapter 2 presents a comprehensive literature review, focusing first on the specific characteristics of the market, then on the autocorrelated nature of smaller markets, and finally on how news impacts price changes, as evidenced by several studies. Chapter 3 describes the political news data and the price changes of the selected stocks. Chapter 4 reviews the panel data models, discussing their assumptions and the tests used to verify these assumptions. The reader is assumed to have an essential understanding of fixed and random effect models. Chapter 5 presents the results and their interpretation, while Chapter 6 offers a detailed conclusion.

Chapter 2

Literature review

Firstly, a brief understanding of the researched market is essential for our study. In examining the PSE, we investigate whether foreign stock markets or local events primarily influence the price movements. This analysis is divided into two sections. The first section addresses market correlation, and the second focuses on volatility spillover effects. This enables the potential explanations of price changes of stocks at the PSE to be provided. Following this analysis, we shift our focus to the impact of news on stock markets. This literature review structure facilitates a comprehensive understanding of the market dynamics and their influences, as well as the specific impact of news on price changes, which is the primary focus of our research.

2.1 Correlation of Stock Markets

Several studies have examined the efficiency of the Czech stock market and its correlation with other European stock markets. This section presents the key findings in chronological order.

Rockinger & Urga (2001) investigated transition economies and found that the Czech market exhibited high predictability, with peaks in November 1994 and April 1997. In contrast, the Hungarian market demonstrated lower predictability, attributed to its higher liquidity and longer operational history.

Their study indicated that the US market did not significantly affect the Polish, Hungarian, and Czech markets, possibly due to geographical distance. Interestingly, the British stock market significantly influenced the Czech, Polish, and Hungarian markets, while the German stock market's influence waned after the spring of 1995.

Korhonen & Peresetsky (2016) studied the correlation between emerging markets, particularly Russia. In 1997, the Czech market had minimal correlation with the Polish, Hungarian, Russian, and German markets. However, from 2004 to 2006, there was an increasing correlation between Russian and Eastern European stock markets. Fedorova (2011) supported this trend, noting increased shock transmission between similar sectors after Poland, Hungary, and Czechia joined the EU, indicating growing integration and susceptibility to contagion within European stock markets.

From 2009 to 2012, the Czech market showed stronger correlations with Poland, Hungary, and Germany, although still lower than correlations among developed markets like the UK and Germany. Korhonen & Peresetsky (2016) attributed this trend to factors such as the synchronisation of closing times between the German and UK markets, highlighting a more synchronised global market influence. They also observed that since 2003, the Polish market had become increasingly correlated with the German market, implying that local news was becoming less relevant. This underscores the potential importance of local news for the Czech market, as its smaller size suggests that local events may significantly impact market dynamics, particularly in intraday trade.

2.2 Volatility Spillover Effects on Stock Markets

The previous section focused on market correlation, concluding that the PSE is not yet fully integrated and thus more prone to local events. This section examines the influence of volatility within global financial markets and the transmission of shocks across these markets, known as volatility spillover effects.

Ng (2000) and Li & Giles (2015) studied the magnitude and evolving nature of volatility spillovers in stock markets of the USA, Japan, and various Pacific region countries. Ng (2000) concluded that bear markets (markets with declining prices) are more contagious than bull markets (markets with rising prices), consistent with findings by Bae & Karolyi (1994) and De Santis & Gerard (1997). This is particularly relevant as our study focuses on a generally bull market period. Ng (2000) also found that while the global impact, particularly from the US, is significant, regional influences from Japan remain substantial for the Pacific-Basin markets.

Li & Giles (2015) provided a detailed examination of volatility spillovers, concluding that in emerging markets, past price shocks have a more significant and persistent impact on current price volatility than in developed markets. This highlights the greater sensitivity of emerging markets to historical shocks. Contrarily, Yin et al. (2020) found that bear and bull markets significantly increased volatility spillover at the Shanghai Stock Exchange, with a more substantial influence from bull markets.

Research on other developing markets has also been conducted. Ahmed & Abou-Zaid (2011) studied the transmission of daily stock index volatility from US and UK financial markets to selected MENA emerging markets such as Egypt, Israel, and Turkey. They found that the US market significantly affects volatility in Israeli and Egyptian markets, whereas the UK market does not.

However, they support the claims above of self-influencing market volatility with a dominant lag effect in the two stock markets of Israel and Egypt.

Volatility and error transmission within European stock markets have been extensively studied. Booth et al. (1997) focused on Nordic equity markets and concluded that past values strongly influence market price volatility, with bad news having a more pronounced effect than good news. Koulakiotis et al. (2009) examined volatility and error transmission in Scandinavian, Germanic, and French stock markets area, finding that Finnish and Danish portfolios transmit volatility to Swedish portfolios, contrary to findings of Booth et al. (1997).

Regarding the Germanic stock market area, Koulakiotis et al. (2009) identified Swiss portfolios as the primary source of volatility. In the French stock market area, Paris, Amsterdam, and Brussels were identified as primary sources of volatility for Milan and Madrid. Notably, the Spanish portfolio received substantial negative volatility from other markets, while the Italian portfolio received positive information.

Extending to European bond markets, Christiansen (2007) found that volatility in several European bond markets is affected by US and European bond market volatility. She distinguished between global, regional, and local effects, revealing that regional effects are most important for EMU countries, while local effects are more pronounced in non-EMU countries like Czechia.

As mentioned by Li & Giles (2015) and Booth et al. (1997), small and developing markets are prone to autocorrelated price changes. The autocorrelation of PSE prices was confirmed by Borovička (2011), who found that the GJR-GARCH(2,2) model was the most appropriate for estimating the logarithms of PX index revenues, indicating the autocorrelated nature of the PSE.

2.3 Impact of News on Stock Markets

The next area of research examines the impact of news on financial markets. Key studies for our analysis are van der Merwe & vd M. Smit (1997) and French

& Roll (1986), whose findings on news impact and the magnitude of open-to-close and close-to-open price changes will be compared with our results. To set the stage, we summarise the key findings in the literature on the impact of news on market prices.

Fundamental research by Roll (1984) investigated how weather forecasting news affects the pricing of frozen concentrated orange juice futures. He found that weather, especially cold temperatures, significantly influences futures prices, with temperature forecast errors affecting price changes more than errors in rainfall prediction. However, exchange-imposed limits on price movements create inefficiencies, allowing temperature surprises to temporarily predict price changes. Despite the weather being crucial for orange production, it explains only a tiny portion of futures price variability, indicating significant unexplained price volatility.

Regarding macroeconomic news, Cutler et al. (1998) revealed that it could only explain one-third of the New York Stock Exchange return variance. They highlighted the difficulty in explaining up to half of the variance in stock prices based solely on publicly available news related to fundamental values. They expressed scepticism about the hypothesis that stock prices move in response to news not observed by market investigators, suggesting that significant news would likely leave traces in official economic statistics or media reports.

Similarly, Mitchell & Mulherin (1994) reached comparable conclusions regarding macroeconomic announcements, stating that "neither trading volume nor market returns are significantly different on days having macroeconomic announcements" (Mitchell & Mulherin, 1994, p. 949). However, they also studied the impact of the amount of news published on trading activity and price movements. They found a significant relationship between the number of news items and market activity, observing day-of-week patterns for both variables.

van der Merwe & vd M. Smit (1997) measured the day-of-week pattern, finding that the null hypothesis of equal means across trading days could not be rejected for Domestic Political news items. However, for the volume traded on the JSE, the null hypothesis was rejected, indicating a significant increase in volume from Monday to Friday. This pattern could not be attributed to a rise in political news activity, as the number of domestic political news items remained consistent throughout the week. The observed day-of-week effect on the JSE differed from patterns on the New York Stock Exchange, where previous studies found a peak in trading volume from Monday to Wednesday with a decline towards Friday. Additionally, the study noted that day-of-week effects varied between Domestic Political news and firm-specific or macroeconomic news events, likely due to the unpredictable nature of political news compared to the more controlled release of firm-specific information.

Ederington & Lee (1995) analysed how interest rate and foreign exchange futures market prices adjust to new information from scheduled macroeconomic news releases in seconds. They concluded that market prices begin adjusting almost immediately, typically within the first 10 seconds, with significant adjustments usually completed within 40 to 50 seconds. Evidence suggests an initial overreaction within the first 40 seconds, followed by a slight correction in the second or third minute, while volatility remains elevated beyond three minutes, indicating ongoing reassessment by traders.

French & Roll (1986) observed significant differences in volatility between open-close and close-open periods, specifically trading and non-trading hours. Their research, which analysed hourly return variances of stocks listed on the New York and American Exchanges from January 1963 through December 1982, found that hourly variance during a trading day was approximately 70 times larger than during a weekend non-trading hour. They attributed this stark contrast to differences in the flow of information during trading and non-trading hours, suggesting that most information is private rather than public. Minor variances over exchange holidays supported this claim.

Damodaran (1989) examined the impact of the timing of information releases, such as earnings and dividend announcements. He attributed negative returns on Mondays to Friday news being associated with more quarterly earnings and dividend per share declines than any other day. This practice is not restricted to company size, but smaller companies tend to have slower price adjustments, extending price changes to the next day.

Merello et al. (2018) investigated the potential impact of new information on stock prices and its correlation with recently published aggregate news. They concluded that while news articles can accurately predict past stock price movements, their predictive performance diminishes significantly when forecasting future movements.

Contrary to these findings, Khan et al. (2022) used machine learning to analyse the impact of social media and financial news data on stock market prediction accuracy over ten subsequent days. They found that utilising news and social media as external factors aids in predicting stock market trends. Social media significantly influences stock prediction on day 9, while financial news has more substantial effects on days 8 and 9. Combining sentiments from both sources led to decreased accuracy initially but improved overall accuracies after day 3.

Summary of Findings and Implications for the PSE

In this chapter, we explored the behaviour of developing markets with a particular focus on the PSE. The evidence suggests that the PSE remains less interlinked with global markets, which implies a significant potential for local news to influence market prices.

The study period coincides with a generally bullish market in Western countries. During bullish periods, volatility spillovers are typically smaller, meaning that the PSE might experience less volatility transmission from global markets, making local factors more impactful. As a developing market, the PSE is expected to exhibit significant autocorrelation, meaning past price shocks have a more substantial and lasting impact on current price volatility. This characteristic suggests that historical prices on the PSE could provide valuable information for predicting future price movements.

As discussed, macroeconomic news tends to explain only a portion of price variance in larger, more integrated markets, supporting the idea that local events and news could play a more substantial role in the PSE. Nevertheless, testing the hypothesis of the insignificance of macroeconomic news on stock price changes remains essential.

On the other hand, political news has the potential to significantly influence price changes, as political events tend to have a direct and substantial impact on market activity. We hypothesise that political news will better predict price changes on the PSE compared to generic published news.

Chapter 3

Dataset

This chapter provides a detailed description of the datasets utilized in our analysis. We begin by defining the explanatory variables employed in our study, outlining their structure and relevance. Next, we examine the data related to share prices, analyzing their characteristics and patterns. Finally, we explore the day-of-week effects of price changes and the news volume, including assessing their correlation.

3.1 News Dataset Description

This thesis aims to study the impact of domestic political news on the PSE. Since van der Merwe & vd M. Smit (1997) studied similar phenomena, our data collection was analogous to theirs. Therefore, an external and singular source of news items was employed for this purpose. In our case, it was the Česká Tisková Kancelář (ČTK).

The ČTK classifies news into several classes. Region, Service, News type, and Categories can be selected. Each class has multiple subclasses, detailed in the appendix. News items may belong to various classes and subclasses.

Our primary explanatory variable, the amount of daily published political news, is N_t^P, where $t = 1,2, \ldots, 734$, corresponding to the 734 workdays in our study period. The daily amount of macroeconomic news is denoted as N_t^M, with t ranging similarly. The total amount of daily news published is denoted as N_t^A, with t also ranging from 1 to 734.

To define N_t^P, we selected the following subclasses from ČTK's classification: in Region, it is 'Czech Republic'; in Services, it is 'Domestic'; in News type, it is 'News'; and in Categories, it is 'Home politics'. Our primary explanatory variable is the amount of published domestic political news per day.

For N_t^M, the subclasses used were: in Region, it is 'Czech Republic'; in Services, it is 'All services'; in News type, it is 'News'; and in Categories, it is 'Makroekonomika'. This variable represents the amount of macroeconomic news published throughout the time.

Finally, N_t^A is defined using the following classification: in Region, it is 'All regions'; in Services, it is 'All services'; in News type, it is 'All news types'; and in Categories, it is 'All categories'. This variable represents the amount of all news published by ČTK in the given period.

Given that the stock market operates only on workdays from 8:50 AM to 4:10 PM, we introduce a revised measure of time to reflect this trading schedule. Consequently, we define a day according to workday trading hours. Figure 3.1 illustrates the discrepancy between the conventional calendar day division and our adapted workday-based division.

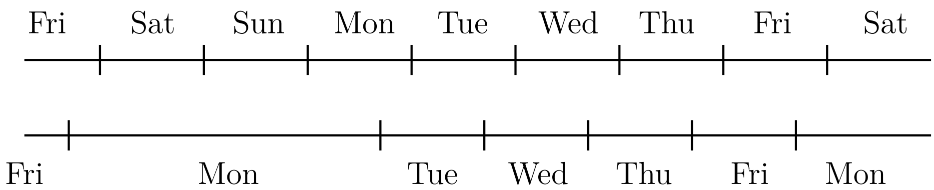

Figure 3.1: Week divided into workdays

On the top line, we observe the time divided into days. On the bottom line, the time is divided into our defined workdays.

Our dataset is structured around a trading week of five workdays, where each trading day starts at 4:10 PM on the previous workday and ends at 4:10 PM on the current workday. Consequently, Monday represents the most extended workday, including the entire weekend. This framework is employed because the stock exchange operates exclusively on workdays. A workday is considered part of the next trading day if it does not serve as a trading day. For example, if Monday is a national holiday, the period from Friday afternoon through the entire weekend and Monday is incorporated into Tuesday's trading day.

Since French & Roll (1986) suggested the different behaviour of price volatility between open-to-close and close-to-open hours, we divide each trading day into non-trading and trading periods. Specifically, the non-trading period spans from 4:10 PM to 8:50 AM, denoted as t, c, while the trading period spans from 8:50 AM to 4:10 PM, denoted as t, o. Consequently, the total amount of political news N_t^P on day t can be expressed as the sum of political news during the non-trading and trading periods, i.e., $N_{t,c}^P + N_{t,o}^P = N_t^P$, where t ranges from 2 to 734. The same decomposition applies to N_t^M and N_t^A.

We begin our analysis with $t = 2$, corresponding to Monday, the 3rd of May 2021. Data for the preceding Friday, the 30th of April 2021, is unavailable until 4:10 PM. Our study period extends from the 30th of April 2021, 4:10 PM, to the 31st of March 2024, 4:10 PM.

During this period, ČTK published a total of 296,413 news items, of which 35,799 are categorized under our predetermined filters for N_t^P. Regarding the primary classification by Services, 134,925 news items were labelled as Domestic, 85,217 as International, and 89,462 as Economics.

Statistics	2021	2022	2023	2024	Summary
Number of Trading Days (T)	168	252	250	63	733
Number of Non-trading Days	77	113	115	28	333
$\sum_{t=2}^{T} N_{t,o}^{P}$	3975	6889	6160	1483	18507
$\sum_{t=2}^{T} N_{t,c}^{P}$	3851	6390	5825	1226	17292
Mean of $\sum_{t=2}^{734} N_{t,o}^{P}$	24	27	25	24	25
Median of $\sum_{t=2}^{734} N_{t,o}^{P}$	22	26	25	22	24
$\text{Var}\left(N_{t,o}^{P}\right)$	90	143	90	70	108

Table 3.1: Descriptive Statistics of Amount of Political News

Descriptive statistics of N_t^P from the 30th of April 2021, 4:10 PM, to the 31st of March 2024, 4:10 PM.

Our primary explanatory variable is N_t^P, representing the daily amount of political news. This section focuses on examining its characteristics. Table 3.1 presents basic descriptive statistics for N_t^P. It is important to note that the years 2021 and 2024 are incomplete, which results in comparatively lower absolute counts of news items for these years than for 2022 and 2023.

The year 2022 stands out due to the exceptionally high average amount of political news during trading hours and increased variance in the number of news items across trading days. This spike can be attributed to significant local events, such as the presidential and communal elections, as well as major global events, like the war in Ukraine and the death of Queen Elizabeth II.

Figure 3.2 illustrates the most eventful days within the specified period, showing the daily count of political news items. The red line represents the monthly mean of political news. The most eventful days, with over 100 news items, were the 10th of October 2021 – 112 (hospitalisation of Czech president Zeman), the 24th and 25th of February 2022 – 139 and 106, respectively (full-scale Russian invasion of Ukraine), then the 25th of September 2022 – 135 (announcements of results of Czech communal elections) and the 29th of January 2023 – 116 (announcements of results of Czech presidential elections).

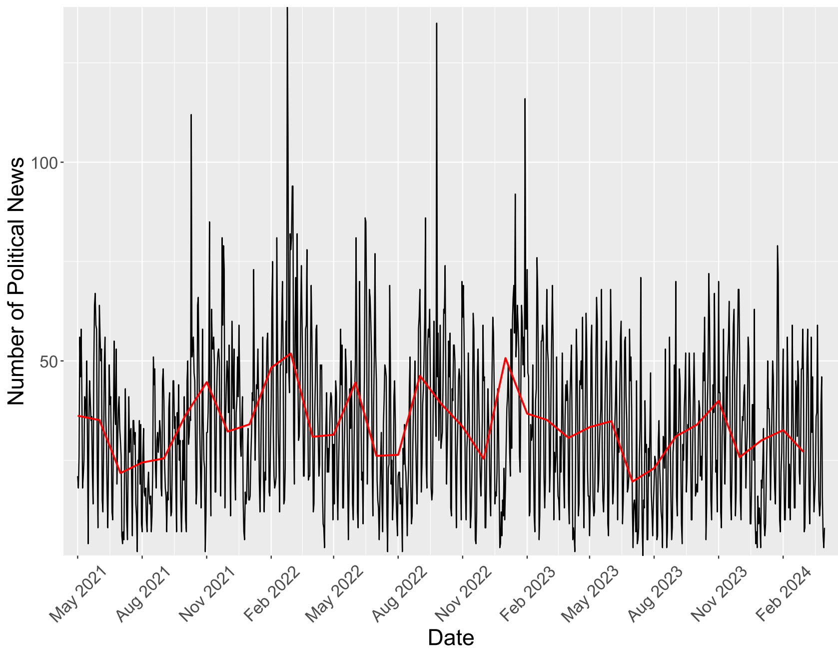

Figure 3.2: Amount of Political News over Time

The black line indicates the amount of political news daily. The red line connects the monthly averages of amounts of news.

Besides the already described data that we mined from the ČTK (2024) database and used for defining N_t^P variable, we also gathered data for the variables N_t^A and N_t^M. These variables, however, are not as central to our research as N_t^P is. Therefore, we do not explore them in as much detail to maintain the readability and clarity of our text.

3.2 Shares Dataset Description

As we were focused on the independent variable in this research (i.e. political news amount), let us now shift our focus to the dependent variable: share prices variance at PSE. It is a small stock exchange, so we picked just the daily traded stocks on the Prime Market. One stock was not traded for one day (Kofola, 22nd of November 2023) but still was left in our analysis. In alphabetical order, these stocks are: Colt CZ Group (Colt), Erste Group Bank

(Erste), Kofola ČeskoSlovensko (Kofola), Komerční banka (KB), MONETA Money Bank (Moneta), Skupina ČEZ (ČEZ), and Vienna Insurance Company (VIG).

Of the seven companies in question, one is engaged in the production of arms (Colt), one in the field of energetics (ČEZ), one in the food industry (Kofola), three in the banking sector (Erste, KB, Moneta), and the final company in the insurance industry (VIG).

We gathered the data about open and closed prices at the Fio (2024) and Burza cenných papírů Praha (2024) websites.

Firstly, we look at the basic statistics about price changes between the markets' open and close hours. Based on the findings of French & Roll (1986), these changes should be more significant in magnitude than the price changes between closing and opening hours.

Company	Variance	Max Negative δ	Max Positive δ
Colt	1.700413	-6.181818	10.861423
ČEZ	2.541598	-8.733624	8.728448
Erste	2.883161	-8.772360	9.460317
Kofola	1.941178	-7.908497	6.493506
KB	0.942414	-4.332130	4.115226
Moneta	1.144934	-4.447045	6.083650
VIG	1.242481	-5.629139	5.140962

Table 3.2: Descriptive Statistics of the Percentage Changes in the Prices of Opening and Closing Hours

Descriptive statistics of the percentage changes in the price of predetermined titles from the 30th of April 2021, 4:10 PM, to the 31st of March 2024, 4:10 PM, during trading hours.

Table 3.2 presents descriptive statistics of price changes during trading hours. We do not include averages because averaging daily percentage changes does not indicate whether prices ultimately increased, decreased, or remained the same.

The stocks with the highest price change variance are ČEZ and Erste. Notably, Colt, ČEZ, and Erste experienced the most significant upward price swings in a single trading day. Conversely, ČEZ, Kofola, and Erste recorded the greatest downward price swings within one trading day. On the other hand, KB, Moneta, and VIG demonstrated the highest stability. This is an intriguing finding, as the banking sector, the only sector with multiple companies listed on the Prime Market, cannot be easily generalized for stability or volatility based on these results.

Secondly, we examined the statistics of price changes between the markets' close and open hours. We would have observed even more significant downward price shifts without any adjustments. This is caused by ex-dates, which lead to price drops in the size of the dividend amount. Table 3.3 then depicts the descriptive statistics for non-trading price changes without the price drops caused by dividends.

Company	Variance	Max Negative δ	Max Positive δ
Colt	0.513566	-5.078125	4.743083
ČEZ	0.461578	-6.702413	4.303511
Erste	0.708488	-4.840941	5.104408
Kofola	0.409670	-2.800000	2.500000
KB	0.471267	-4.878049	4.590354
Moneta	0.414675	-4.822335	3.395473
VIG	0.656687	-4.889590	3.880071

Table 3.3: Descriptive Statistics of the Percentage Changes in the Prices of Opening and Closing Hours

Descriptive statistics of the percentage changes in the price of predetermined titles from the 30th of April 2021, 4:10 PM, to the 31st of March 2024, 4:10 PM, during non-trading hours.

We observe more minor differences in values across the stocks. Interestingly, Kofola exhibits much more stability during non-trading hours than trading hours. The variances of price changes are significantly lower for all the stocks we observed during non-trading hours. This observation aligns with the findings of French & Roll (1986), who estimated that the average variance during average non-trading hour is 71.8 times smaller than during average trading hour. However, in our study, the non-trading hour variance is only 12.8 times smaller than the trading hour variance.

We can reject the hypothesis that this result indicates a more significant induced volatility potential during non-trading hours at the PSE due to the impact of political news on price changes. This conclusion is supported by the fact that the hourly average of $N_{t,c}^{P}$ is 65 times smaller than the hourly average of $N_{t,o}^{P}$. Instead, this phenomenon could be attributed to the inefficiency of the PSE, as the price changes are autocorrelated. The results in Chapter 5 support this claim.

3.3 Day-of-week effect

Not only do we study the impact of N_{t}^{P} on price changes at PSE, but we are also interested in the day-of-week effect of the price change. Chapter 4.1 defines price percentage change, which we use as our primary explained variable. The histograms in Figure 3.3 and Figure 3.4 depict the mean price percentage change during t, o and t, c, respectively.

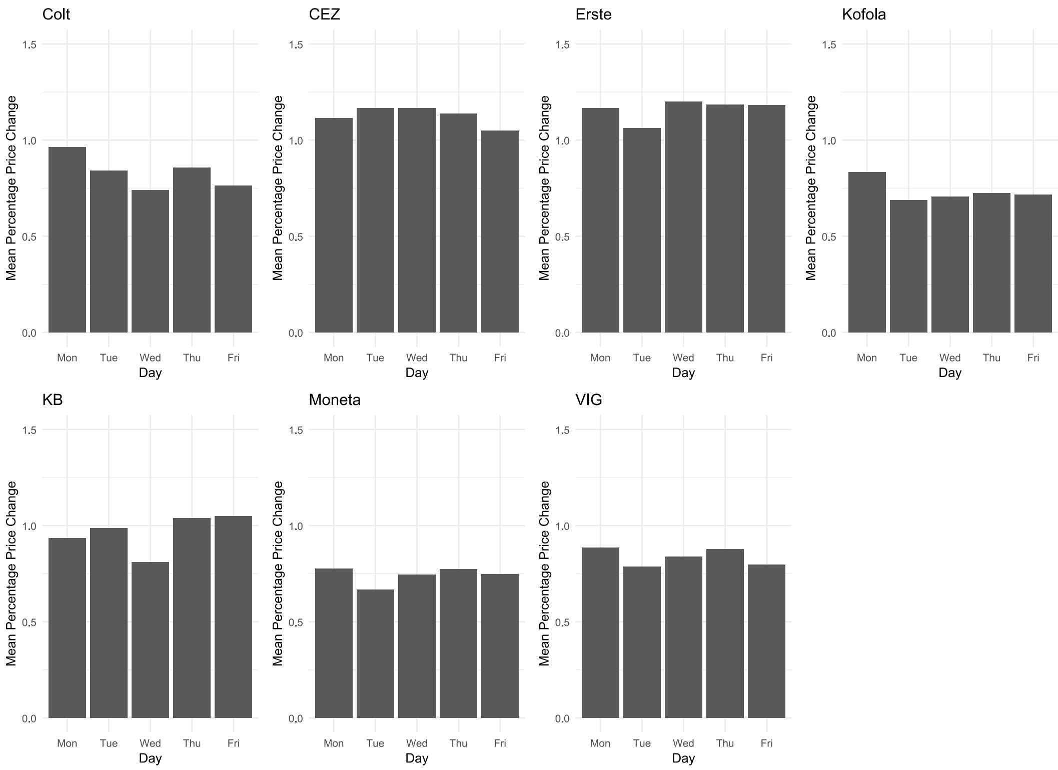

Figure 3.3: Distribution of Mean Percentage Price Change during t, o

Histogram depicts the distribution of stocks' mean percentage price change during trading hours.

Figure 3.3 demonstrates that the percentage price changes during t, o for the companies ČEZ, Erste, Kofola, Moneta, and VIG have relatively stable mean, contrary to Colt, or KB, which display days that appear to exhibit significantly different behaviours. In the case of Colt, a pattern emerges where the price changes from Monday to Wednesday diminish before exhibiting a slight increase on Thursday and lower changes on Friday again. Conversely, the percentage price change for KB appears to rise slightly throughout the week, except for a significant drop on Wednesday.

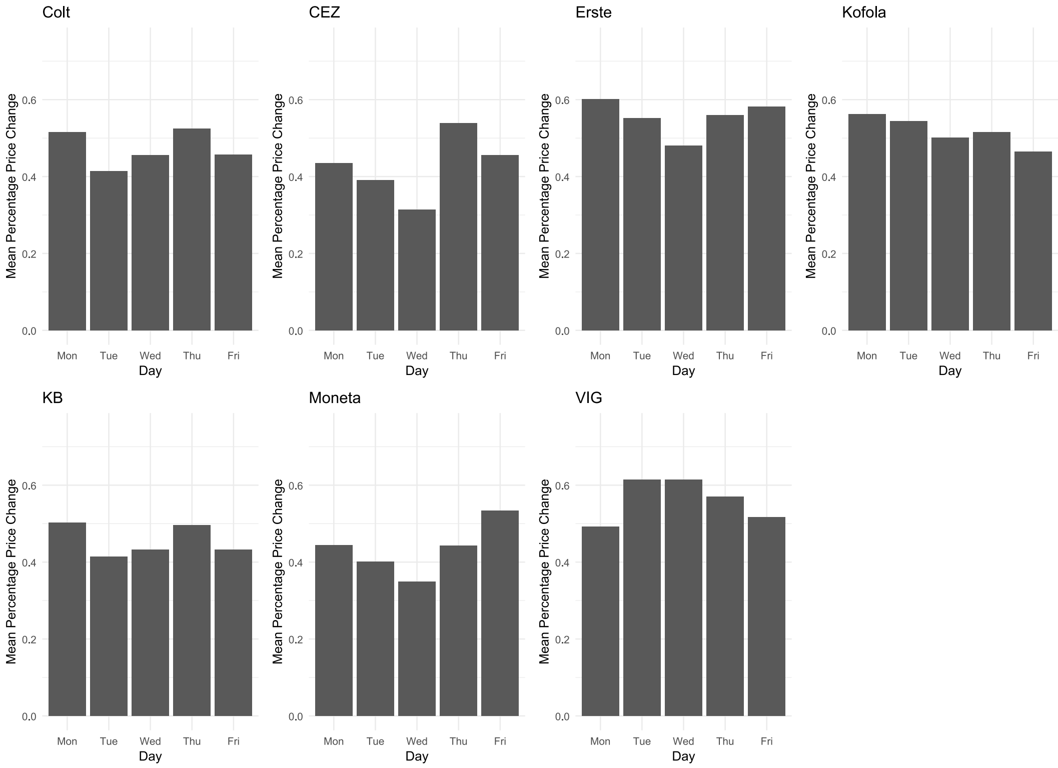

Figure 3.4: Distribution of Mean Percentage Price Change during t, c

Histogram depicts the distribution of stocks' mean percentage price change during non-trading hours.

Figure 3.4 implies that mean percentage price changes appear more volatile during non-trading hours than during trading hours. The most significant differences between values of certain days are observed for the ČEZ and the Moneta, where the rise from Wednesday to Thursday for the ČEZ and from Wednesday to Friday for the Moneta is around 0.2 percentage points.

The mean price change of the remaining stocks was less volatile than these two. However, each of the remaining stocks recorded changes in values for different days around 0.1 percentage points, with more significant differences between every workday. This reinforces the earlier statement that non-trading days have a more volatile mean of percentage price changes.

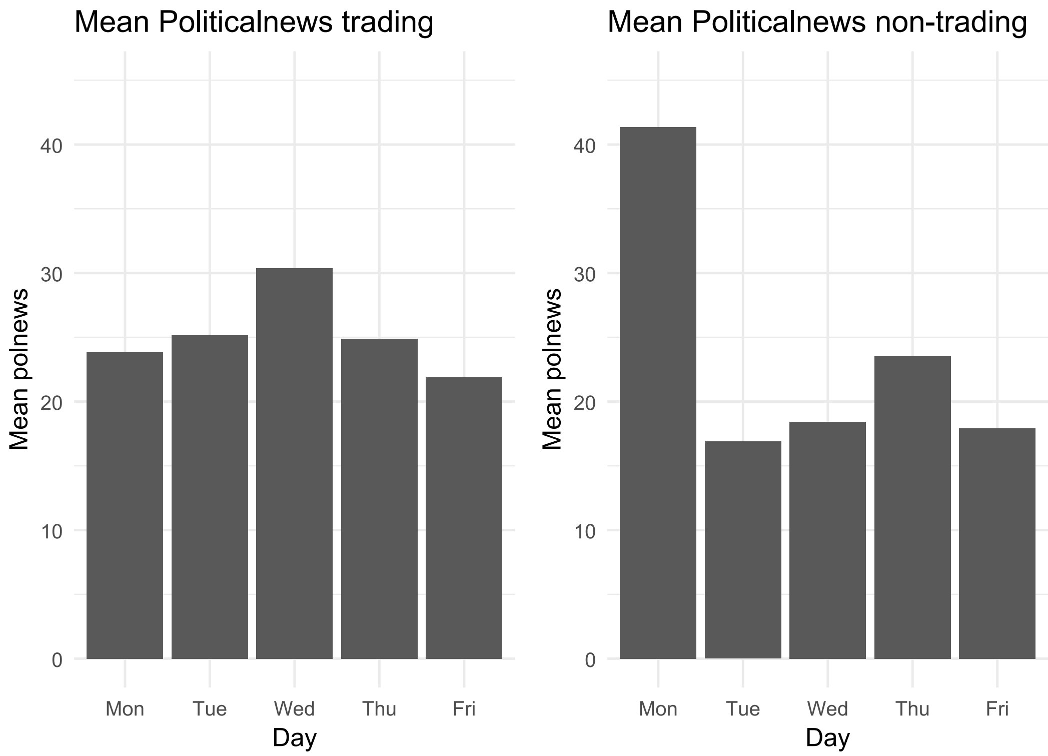

Figure 3.5: Daily Distribution of N_t^P

Histogram depicts the daily distribution of means of $N_{t,o}^P$ on the left and of $N_{t,c}^P$ on the right.

Figure 3.5 shows that the day-of-week effect for changes in the mean percentage price changes is inconsistent with the day-of-week effect for the workday means of the N_t^P. As we can see, there is a tendency for the variable $N_{t,o}^P$ to increase at the beginning of the week, peak on Wednesday and then fall to its lowest on Friday. As we described earlier, this is not true for the mean percentage price changes. The trend of the mean of $N_{t,o}^P$ differs from van der Merwe & vd M. Smit (1997) findings about political news in South Africa. However, it is very similar to the trend of volume traded on the New York Stock Exchange studied by Mitchell & Mulherin (1994). The pattern for $N_{t,c}^P$ is distorted by the amount of news allocated to the Monday, as it includes not only Friday afternoon (as every other day consists of the afternoon of the previous working day) but also all the news from Saturday and Sunday. Moreover, the peak on Thursday's non-trading hours can be explained by the momentum of Wednesday's news volume on the trading day, as it can be expected that the news will continue to be published in the afternoon.

Based on these findings, the variables $N^P_{t,o}$ and $N^P_{t,c}$ do not seem to be correlated with the percentage prices changes during trading and non-trading hours. Therefore, we present Table 3.4 to check if the statement above holds true.

Company	$N^P_{t,o}$	$N^M_{t,o}$	$N^A_{t,o}$
Colt	0.108065	-0.011947	0.121477
ČEZ	0.096460	0.087228	0.071500
Erste	0.208520	0.088777	0.238105
Kofola	0.121690	0.037452	0.089081
KB	0.246403	0.104471	0.222102
Moneta	0.120276	0.089957	0.067328
VIG	0.104206	0.064229	0.089757

Table 3.4: Correlation table of news and trading hour price change

Correlations of news variables with the companies' price change during trading hours.

We observe that the correlations are nowhere near the levels found by van der Merwe & vd M. Smit (1997) in their study. The only similarity is that the correlation of price variance with $N^P_{t,o}$ is higher or very similar to the correlations with $N^A_{t,o}$. We also observe that $N^M_{t,o}$ is usually the least correlated with price change of the three news categories. This seems to follow the claims of Mitchell & Mulherin (1994).

The two most significant correlation coefficients in the $N^P_{t,o}$ column are related to the banking sector. However, Moneta's correlation coefficient is only half that of Erste. Colt, ČEZ and VIG have the lowest correlation coefficients in the $N^P_{t,o}$ column. Colt has the most significant coefficient in the $N^A_{t,o}$ column. Although ČEZ's and VIG's highest correlation coefficient is in the column with the $N^P_{t,o}$ variable, the ratio of $N^M_{t,o}$ to $N^P_{t,o}$ for ČEZ is the highest of all stocks. Nevertheless, the value in the $N^M_{t,o}$ column is still small for ČEZ.

Company	$N^P_{t,c}$	$N^M_{t,c}$	$N^A_{t,c}$
Colt	0.097632	0.067014	0.081892
ČEZ	0.050131	0.122619	0.024627
Erste	0.114306	0.116150	0.105416
Kofola	0.037941	0.011898	0.031876
KB	0.112499	0.088505	0.093116
Moneta	0.02713	0.030508	0.039590
VIG	-0.010537	0.005094	-0.034518

Table 3.5: Correlation table of news and non-trading hour price change

Correlations of news variables with the companies' price change during non-trading hours.

Next, we present Table 3.5, which depicts the statistics during the non-trading days. The differences between these tables are considerable. The correlation coefficients in the $N^P_{t,c}$ column are mostly negligible, except for Erste and KB. The same applies to the $N^A_{t,c}$ column, where values closer to 0.1 can also be found at ČEZ. However, compared to the other two columns, the relative size of the correlation coefficient in the $N^M_{t,c}$ column increased considerably for the ČEZ, Erste, and KB shares.

Chapter 4

Methodology

In this chapter, we present the methodology employed in our study. We begin by defining our key explanatory variable. We then explore the use of panel data models, detailing their assumptions and the tests conducted to verify these assumptions. Following this, we introduce our specific panel data models and address their limitations. To enhance our analysis's robustness, we shift our focus to dynamic panel data models, which we define and justify as a superior fit for our dataset. The same notation of days as in Chapter 3 applies here.

4.1 Dependent Variable

As we aim to study the impact of political news on market price volatility, we shall first define how to calculate it. The variance of share price changes can represent share price volatility. Wiggins (1992) and van der Merwe & vd M. Smit (1997) employed this equation (4.1) in their study to estimate the price variance,

$$\sigma_t^2 = \left(\ln\left(\frac{P_{t,c}}{P_{t-1,c}}\right)\right)^2, \tag{4.1}$$

where σ_t^2 represents the price variance estimator of the price change variance between close hour for the day t and $t-1$. The closing price at day t is represented by $P_{t,c}$, as $t = 2,3,\ldots,734$ since we do not possess data of price $P_{t-1,c}$ for the day $t = 1$. In our case, however, this estimator is deemed problematic due to its non-linearity. As we study this topic in more depth, we want to interpret the magnitude of the impact of the amount of political news published on the percentage price change.

Hence, we introduce different volatility estimators in equation (4.2),

$$\begin{aligned} \sigma_{t,o} &= \left| \frac{(P_{t,c} - P_{t,o})}{P_{t,o}} \cdot 100 \right|, \\ \sigma_{t,c} &= \left| \frac{(P_{t,o} - P_{t-1,c})}{P_{t-1,c}} \cdot 100 \right|, \end{aligned} \tag{4.2}$$

where $P_{t,o}$ and $P_{t,c}$ denote the opening and closing price on day t, respectively. Then $\sigma_{t,o}$ and $\sigma_{t,c}$ denote the estimators of price standard deviation of the price change between the open and close hours and close to open hours for the day t, respectively as $t = 2{,}3, \ldots, 734$.

On the one hand, it is more trivial; on the other, it is linear in interpretation. With these $\sigma_{t,o}$ and $\sigma_{t,c}$ variables as a dependent variable in our models, we can easily interpret the impacts of independent variables. Suppose our slope parameter for the independent variable $Z_{i,t}$ equals 1. In that case, it means that a positive change by one unit in that variable causes a positive change in the dependent variable also by one unit. That would mean that the price change is equal to 1 %.

4.2 Panel Data Models

This thesis aims to estimate political news's effect on several stocks' price variance simultaneously, so panel data is appropriate for this analysis. The general model for panel data is specified as

$$\mathbf{y} = \mathbf{X}\beta + \mathbf{u}, \tag{4.3}$$

where $\mathbf{y}$ is an $NT \times 1$ vector of stacked $y_{i,t}$, representing the time- and individual-specific dependent variable. $\mathbf{X}$ is an $NT \times (K+2)$ matrix of stacked $[1, X_{1,i,t}, X_{2,i,t}, \ldots, X_{K,i,t}, 1]$, which includes the time- and individual-specific explanatory variables, with the first and last columns being ones for the intercept and unobserved error, respectively. The vector β is a $(K+2) \times 1$ vector of coefficients $[\beta_0, \beta_1, \beta_2, \ldots, \beta_K, \alpha_i]$, representing the intercept, slope parameters, and the time-invariant, individual-specific unobserved error. Finally, $\mathbf{u}$ is an $NT \times 1$ vector of stacked $u_{i,t}$, representing the time- and individual-specific idiosyncratic error. In this context, N denotes the number of companies tested, which is 7; T represents the number of trading days, i.e. 733; and K is the number of explanatory variables.

Firstly, we want to inspect the impact of N_t^P on $\sigma_{t,o}$ and $\sigma_{t,c}$. In our case, the models based on the model (4.3) then are,

$$\sigma_{i,t,o} = \beta_0 + \beta_1 \ N_{t,o}^P + \beta_2 \ N_{t,o}^M + \beta_3 \ N_{t,o}^A + \sum_{j=1}^{4} \gamma_j D_{j,t} + \alpha_i + u_{it}, \tag{4.4}$$

$$\sigma_{i,t,c} = \beta_0 + \beta_1 \ N_{t,c}^P + \beta_2 \ N_{t,c}^M + \beta_3 \ N_{t,c}^A + \sum_{j=1}^{4} \gamma_j D_{j,t} + \alpha_i + u_{it}, \tag{4.5}$$

where t = 2,3,..., 734, j = 1,2,..., 4, as the number of dummy variables, and i = 1,2,..., 7, as the number of companies. The variable D_j, t denotes the dummy variable for days, hence, $D_{1,t}$ denotes Tuesday, $D_{2,t}$ denotes Wednesday, $D_{3,t}$ denotes Thursday, and finally $D_{4,t}$ denotes Friday. We have just four dummy variables for days to avoid the dummy variable trap. If we included all days, we would achieve perfect multicollinearity, leading to biased and inconsistent estimators of the population parameters. The γ_j stands for the slopes of the dummy variables.

4.3 Assumtions and Tests

Hausman Test

After defining the model form, we should appropriately select between the suitable models, as there are several possibilities for modelling panel data. Hence, we employ the Hausman test, designed by Hausman (1978), to correctly identify whether the Random effects model (REM) is consistent and unbiased or whether it is more efficient than the Fixed effects model (FEM). The null hypothesis states that the

$$\mathrm{Cov}(\alpha_i, X_{k,i,t}) = 0 \quad \text{for all } k = 1, 2, \ldots, K.$$

The alternative hypothesis states that

$$\mathrm{Cov}(\alpha_i, X_{k,i,t}) \neq 0 \quad \text{for at least one } k = 1, 2, \ldots, K,$$

where K denotes the number of explanatory variables.

If the following assumptions are met, then under the null hypothesis, the REM is not only consistent but also asymptotically more efficient than FEM and under the alternative hypothesis, FEM is solely consistent.

ADF

Firstly, we need to test for stationarity of our data, as our data is in a time series form. We use the test that Dickey & Fuller (1979) proposed, Augmented Dickey-Fuller test (ADF). The zero hypothesis states that

$$|\rho| = 1.$$

The alternative hypothesis states that

$$|\rho| < 1,$$

where ρ represents the slope of Y_{d-1} from equation (4.6) of auto-correlation model,

$$Y_d = \rho Y_{d-1} + \epsilon_d, \tag{4.6}$$

where $d = 1, 2, \ldots$ represents the time in the time series Y_d. Under the null hypothesis, the time series is non-stationary, often described as a random walk. In contrast, under the alternative hypothesis, the time series Y_d converges to a stationary process as d approaches infinity. Chapter 5.1 presents the test results for each company, demonstrating that our data are stationary. Consequently, the regressions should not exhibit spurious relationships due to non-stationarity.

Assumptions of models

To accurately interpret the results from the FEM and REM, it is crucial to ensure that certain assumptions are satisfied to obtain unbiased, consistent, and efficient models with t and F statistics that follow their respective distributions.

The initial assumption of linearity in parameters is met as defined by the model, which ensures that this assumption holds. The second assumption concerning the data to be a random sample in the cross-sectional dimension is also met, as our data are identical to the entire population. Hence, the second assumption also holds. The third assumption concerns multicollinearity. We assess multicollinearity in each model using the Variance inflation factors (VIF), which quantifies to which extent multicollinearity among the independent variables influences the model. As shown in Chapter 5.1, no significant multicollinearity is present in the regressions.

Regarding the strict exogeneity assumption, it is necessary to reject this proposition theoretically and practically. Our variable N_t^P should be theoretically endogenous as politicians and news reporters can react to the same events as the share prices. To test the endogeneity of variables in practice, we plot residuals from the REM following the specification (4.4) and (4.5) to N_t^P, N_t^M and N_t^A. To improve the clarity of this text, the results depicted in Figure A.1,

Figure A.2, Figure A.3 and Figure A.4, are presented in Appendix. These figures provide empirical evidence supporting the endogeneity of the explanatory variables.

Endogeneity causes significant issues, as strict exogeneity is necessary to obtain unbiased and consistent estimates, meaning our model can never be BLUE. Despite these difficulties, we shall continue to estimate models (4.4) and (4.5) using the REM. However, we proceed with great caution in interpreting our results. Robust standard errors are implemented when evaluating our results to address potential biases.

Based on the findings mentioned in the following subsection and the fact that our variables are endogenous, we decided to introduce another endogenous variable: the lagged values of the explained variable. This shifts our panel data into dynamic panel data. As we show in the next section, endogeneity does not cause that much harm in dynamic panel data models.

4.4 Dynamic Panel Data Models

In Chapter 5.1, we test the REM (4.4) and (4.5) for serial correlation by performing the Durbin & Watson (1950) test for serial correlation in panel data models. The null hypothesis states that

$$\rho = 0.$$

The alternative hypothesis states that

$$\rho \neq 0,$$

where the ρ denotes the autocorrelation coefficient in (4.6). Hence, under the null hypothesis, the test indicates no autocorrelation of the explained variable.

The results stated in Chapter 5 suggest that introducing a different equation for a different model is necessary to account for the nature of autocorrelation in our data, following the findings in Chapter 2.1 on the autocorrelated nature of price variance in emerging markets.

Given the endogenous and balanced nature of our panel data, Flannery & Hankins (2013) suggested that the FEM performs best among several advanced models for dynamic panel data. They also suggested that the Blundell Bond estimator (Blundell & Bond (1998)), also known as the system GMM estimator, performs well in estimating the lagged dependent variable in contrast to FEM. "FE is accurate in estimating both the exogenous and endogenous Xs, but not the lagged dependent variable. BB remains the best option for higher levels of endogeneity if the lagged dependent variable is of interest." (Flannery & Hankins, 2013, p. 13). Since we are faced with a long data structure and the explanatory variables are of interest to us, we continue to use only FEM to estimate our panel data. Still, we are well aware that FEM is not unbiased nor consistent. We should also take into consideration the fact that FEM is built mainly for balanced, wide, exogenous panel data. Hence, we will never achieve as good results as Flannery & Hankins (2013) did. Still, we will take the results we obtain as the best we could get from using these methods, and hence, we consider them to be very close to the true values.

Adapting to the results found in Table 5.1 and Table 5.3, we drop the N_t^M variable from our models but introduce lagged values of our dependent variables and news published throughout hours of the previous part of a day. The models that our FEM then follows take the form of,

$$\begin{aligned}\sigma_{i,t,o} = \beta_1\ \sigma_{c,i,t} + \beta_2\ \sigma_{o,i,t-1} + \beta_3\ N_{t,o}^P + \beta_4\ N_{t,c}^P \\ + \beta_5\ N_{t,o}^A + \beta_6\ N_{t,c}^A v + \sum_{j=1}^{4} \gamma_j D_{j,t} + \alpha_i + u_{it},\end{aligned} \tag{4.7}$$

and

$$\begin{aligned}\sigma_{i,t,c} = \beta_1\ \sigma_{o,i,t-1} + \beta_2\ \sigma_{c,i,t-1} + \beta_3\ N_{t,c}^P + \beta_4\ N_{t-1,o}^P \\ + \beta_5\ N_{t,c}^A + \beta_6\ N_{t-1,o}^A + \sum_{j=1}^{4} \gamma_j D_{j,t} + \alpha_i + u_{it},\end{aligned} \tag{4.8}$$

where t = 2,3,..., 734, j = 1,2,..., 4, and i = 1,2,..., 7. We define models like this to capture that prices on such a small market as PSE are strongly autocorrelated, as mentioned in Chapter 2.1.

Chapter 5

Results and Discussion

In this chapter, we present the results of our analysis. We begin by executing the tests outlined in Chapter 4.3 to validate our model assumptions. Following this, we estimate model (4.4) using the REM and model (4.7) using the FEM, providing detailed commentary on the results. We then proceed to estimate model (4.5) with REM and model (4.8) with FEM, offering further analysis and interpretation of these findings.

5.1 Tests of Assumptions

As previously stated in Chapter 4.3, we must first subject our data to a series of tests to identify whether our models' assumptions are met correctly so we can properly evaluate their results.

We applied the Hausman test on the models (4.4) and (4.5). The χ^2 statistics equals $5.4111 \cdot 10^{-13}$ for the first model and $4.3302 \cdot 10^{-12}$ for the second one, with 7 degrees of freedom and a p-value virtually equal to 1. Hence, we fail to reject the null hypothesis at 5 % significance level for both models that

$$\mathrm{Cov}(\alpha_i, X_{k,i,t}) = 0 \quad \text{for all } k = 1, 2, \ldots, 7,$$

where $X_{k,i,t}$ denotes seven matrixes of our three explanatory and four dummy variables.

Regarding stationarity, we conducted the ADF test on every time series of price changes of all stocks. All the values allow us to reject the null hypothesis that the time series has a unit root, as the critical value for a 5 % significance level is -2.86, and our t statistics for every stock is between -19 and -14 for both trading and non-trading hour price variance. Hence, we can claim that our data is stationary.

Next, we wanted to test for multicollinearity. We applied the VIF test on the explanatory variables we used throughout this research. All of the explanatory variables, except for $N^A_{t,c}$, $N^A_{t,o}$ and $N^P_{t,c}$, have the values under 2, showing low multicollinearity. The values for the three variables above are 3.8529, 2.3600 and 2.8827, respectively, exercising moderate multicollinearity that should not cause any problems in our regressions.

When checking for the endogeneity of our explanatory variables, we account for the results from the Hausman test, and hence, we say that if

$$\text{Cov}(\alpha_i, X_{k,i,t}) = 0 \quad \text{for all } k = 1, 2, \ldots, 7$$

then

$$\text{Corr}(X_{k,i,t}, v_{i,t}) \neq 0 \implies \text{Cov}(X_{k,i,t}, v_{i,t}) \neq 0 \implies \text{E}(u_{i,t}|X_{k,i,t}, \alpha_i) \neq 0,$$

$$\text{for all } k = 1, 2, \ldots, 7,$$

where $v_{i,t} = u_{i,t} + \alpha_i$ and $v_{i,t}$ is a composite error.

Therefore, as we show in Figures A.1 and A.2 for trading hours and in Figures A.3 and A.4 for non-trading hours that the variables are correlated with the residuals, as the trend lines are not constant, we can conclude, that our variables are endogenous. Thus, the results of our models should be treated with the utmost caution.

Next, we used the Durbin-Watson test to check for serial correlation in panel models. For the models (4.4) and (4.5) estimated by REM, we obtained the following DW statistics. For the first model, the statistic equals 1.5839.

For the second one, it equals 1.7453. For both, the p-values are close to $2.2 \cdot 10^{-16}$. Hence, we reject the null hypothesis, at a 5 % significance level, that both model parts perform no first-order autocorrelation.

5.2 Trading Hours Price Change Regression Results

Let us first focus on the price change in trading hours. We applied REM on the model (4.4) from Chapter 4.1. The results are shown in Table 5.1. Recall that the model is biased and inconsistent. Hence, we can take these results as a starting point that we can later compare to more reliable results from the dynamic panel data, as stated in Chapter 4.4.

It is also essential to consider the dual impact of political news on share price fluctuations, as these are not solely reflected in the variable N_t^P, but also in variable N_t^A. Hence, a change by one unit in $N_{t,o}^P$ causes a change of the percentage price change by the sum of the slopes for variables $N_{t,o}^P$ and $N_{t,o}^A$.

The estimated model based on the results then takes the following form:

$$\begin{aligned}\hat{\sigma}_{i,t,o} &= 0.259093 + 0.010299\ N_{t,o}^P + 0.000747\ N_{t,o}^M \\ &+ 0.002121\ N_{t,o}^A - 0.105968 D_{1,t} - 0.170604 D_{2,t} \\ &- 0.051817 D_{3,t} + 0.003137 D_{4,t}, \quad t = 2, 3, \ldots, 734.\end{aligned} \tag{5.1}$$

The model estimates that holding all other variables constant, the percentage price change on Monday is 0.11 and 0.17 percentage points higher than on Tuesday and Wednesday, with both days significantly differing from Monday at the 5% significance level.

The results regarding the impact of news align with expectations. The variable $N_{t,o}^M$ shows no significant impact on the dependent variable. That is consistent with the findings of Mitchell & Mulherin (1994) cited in Chapter 2.3. The magnitude and significance of other news types also align with the

	Estimated dependent variable:
	$\hat{\sigma}_{i,t,o}$
$N^P_{t,o}$	0.010299^{***}
	(0.001704)
$N^M_{t,o}$	0.000747
	(0.002045)
$N^A_{t,o}$	0.002121^{*}
	(0.001199)
$D_{1,t}$	-0.105968^{***}
	(0.034252)
$D_{2,t}$	-0.170604^{***}
	(0.042021)
$D_{3,t}$	-0.051817^{*}
	(0.026550)
$D_{4,t}$	-0.003137
	(0.045184)
Constant	0.259093
	(0.202685)
Observations	5,131
R^2	0.027782
Adjusted R^2	0.026454
F Statistic	146.395400^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.1: Results of the REM from the model (4.4)

findings of van der Merwe & vd M. Smit (1997). Nonetheless, we must exercise caution when comparing magnitudes, as these estimations are biased.

Next, we estimate the model (4.7) via FEM. The results are shown in the Table 5.2. Hence, we can write the estimated mode as

$$\begin{aligned}\hat{\sigma}_{i,t,o} = {} & 0.277623\ \sigma_{i,t,c} + 0.181647\ \sigma_{i,t-1,o} + 0.008281\ N^P_{t,o} \\ & + 0.003296\ N^P_{t,c} + 0.000881\ N^A_{t,o} + 0.000415\ N^A_{t,c}v \\ & + 0.034250\ D_{1,t} + 0.001761\ D_{2,t} + 0.022700\ D_{3,t} \\ & + 0.090142\ D_{4,t}, \quad t = 2, 3, \ldots, 734.\end{aligned} \tag{5.2}$$

As stated in Chapter 4.4, this estimation should be more precise than the previous one. While the FEM is known to be less accurate than other models in estimating the slope for lagged values of explanatory variables (Flannery & Hankins, 2013), it is clear that past price changes have the most significant influence on future price changes among our variables. This is consistent with other measurements of price volatility mentioned in Chapter 2.2. Moreover, the slope of the price change between close and open hours is more than thirty times greater than the slope for $N^P_{t,o}$, and the slope of the price change between open and close hours of the previous workday is more than twenty times greater.

The practical impact is significant, as price changes greater than two percentage points are common during non-trading hours. These changes should indicate a 0.5 percentage price change in the following trading day.

The previous day's trading hour price change is also essential in magnitude and statistical significance. While not equal to the actual values of the slopes of prior price changes, both values of the slopes are significant at the 5 % significance level.

As anticipated, introducing previous price change values resulted in a notable reduction in the observed day-of-week effect. At the 10 % significance level, only Friday shows a statistically significant difference from Monday, which is concerning. There is no clear explanation for this result. Neither theory, the data description in Section 3, nor previous model results (5.1) explain why

	Estimated dependent variable:
	$\hat{\sigma}_{i,t,o}$
$\sigma_{i,t,c}$	0.277623***
	(0.055968)
$\sigma_{i,t-1,o}$	0.181647***
	(0.021255)
$N^P_{t,o}$	0.008281***
	(0.001509)
$N^P_{t,c}$	0.003296
	(0.004404)
$N^A_{t,o}$	0.000881
	(0.000623)
$N^A_{t,c}$	0.000415**
	(0.000201)
$D_{1,t}$	0.034250
	(0.070674)
$D_{2,t}$	0.001761
	(0.077224)
$D_{3,t}$	0.022700
	(0.062092)
$D_{4,t}$	0.090142*
	(0.052637)
Observations	5,130
R^2	0.108991
Adjusted R^2	0.106202
F Statistic	62.543610*** (df = 10; 5113)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.2: Results of the FEM from the model (4.7)

Friday should differ in price change by 0.09 percentage points. Therefore, it may be concluded that, due to endogeneity bias, a 90 % confidence interval is insufficient. Hence, we can state that, regarding the price change between open and close hours, the hypothesis of no day-of-week effect of price changes cannot be rejected at the 5 % significance level.

Regarding the slopes of our variables, only $N^P_{t,o}$ is significant. This makes sense, as earlier news should already be accounted for in the close-to-open-hour price change, which is also included in this equation. The estimated slope for $N^P_{t,o}$ differs between the models for panel data and dynamic panel data by 0.002. Despite this being a 20 % difference, it provides important insights regarding the actual values of the slopes for this variable, suggesting that the exact value is around the value of our estimated slope. The magnitude is still considerably high. It would take around 60 $N^P_{t,o}$ or 152 $N^P_{t,c}$ to influence the price change by half a percentage point. Surprisingly, in our dataset, there are just three days during which $N^P_{t,o}$ takes values greater than 60. Days with values more than 48 $N^P_{t,o}$, corresponding to 0.4 % price change, are rare as well, occurring less than 4 % of the time during our study period.

On the other hand, our dataset had four days with values of $N^P_{t,c}$ greater than 152. However, the number of days with values of $N^P_{t,c}$ higher than 91, corresponding to 0.3 % price change, is only six in our researched period. On average, the price change is inflated by 0.21 and 0.08 percentage points due to $N^P_{t,o}$ and $N^P_{t,c}$, respectively.

In this context and compared with the results of REM (4.4), the significance of the $N^P_{t,o}$ and $N^P_{t,c}$ variables is anomalous. At the 5 % significance level, only the $N^A_{t,c}$ variable is significant. Nevertheless, the magnitude of slopes for both of these variables is negligible. To influence the price change by half a percentage point, $N^P_{t,o}$ needs to be over 550 or $N^P_{t,c}$ over 1200. These numbers were never observed throughout our study period. The highest amounts of $N^P_{t,o}$ were 390 on the 24th of February 2022 (the first day of the full-scale Russian invasion) and 879 in $N^P_{t,c}$ on the 26th of September 2022 (Monday after the weekend when the Czech communal and senate elections took place).

5.3 Non-trading Hours Price Change Regression Results

Now, we focus on the REM based on the model (4.5) concerning the close-to-open-hour price changes. The results are shown in Table 5.3. At first sight, we can say that the estimated magnitudes of slopes of our news variables are smaller than for the estimations of the model (4.4) as our estimations for the non-trading hours price change model follow the formula

$$\begin{aligned}\hat{\sigma}_{i,t,c} &= 0.259093 + 0.004524\ N^{P}_{t,c} \\ &+ 0.001357\ N^{M}_{t,c} + 0.000256\ {}_{A}N_{t,c} \\ &+ 0.093677 D_{1,t} + 0.062719 D_{2,t} + 0.050235 D_{3,t} \\ &+ 0.106603 D_{4,t}, \quad t = 2, 3, \ldots, 734.\end{aligned} \tag{5.3}$$

On the other hand, the slopes for the days' dummy variables are more significant. None of them is negative, and at a 5 % significance level, Tuesday and Friday differ significantly from Monday in the values of our explained variable. In this case, Monday's values are smaller by 0.09 and 0.11 percentage points, respectively.

Interestingly, variable $N^{M}_{t,c}$ has greater explanatory power than the variable $N^{A}_{t,c}$. The variable $N^{M}_{t,c}$ is, in this model, the most significant out of the news variables. However, its estimated magnitude is negligible.

	Estimated dependent variable:
	$\hat{\sigma}_{i,t,c}$
$N^P_{t,c}$	0.004524**
	(0.002015)
$N^M_{t,c}$	0.001357***
	(0.000385)
$N^A_{t,c}$	0.000256
	(0.000172)
$D_{1,t}$	0.093677***
	(0.033526)
$D_{2,t}$	0.062719
	(0.040566)
$D_{3,t}$	0.050235
	(0.037493)
$D_{4,t}$	0.106603**
	(0.045518)
Constant	0.281974***
	(0.065119)
Observations	5,131
R^2	0.007654
Adjusted R^2	0.006298
F Statistic	39.511390***
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.3: Results of the REM from the model (4.5)

The impact of the variable $N^P_{t,c}$ in this model is weaker than the impact of variable $N^P_{t,o}$ in the model (4.4). The slope is two and a half times smaller. However, as we mentioned multiple times, this regression is biased. Hence, comparing the magnitude of slopes is less meaningful.

Thus, we now shift toward more reliable estimations that the FEM following the second part of the equation (4.8) should provide us. The results are shown in Table 5.4 as the estimated model based on them takes form:

$$\begin{aligned}\hat{\sigma}_{i,t,c} &= 0.113491\ \sigma_{i,t-1,o} + 0.084640\ \sigma_{i,t-1,c} + 0.003115\ N^P_{t,c}\\ &\quad + 0.001074\ N^P_{t-1,o} + 0.000311\ N^A_{t,c} + 0.000500\ N^A_{t-1,o}\\ &\quad + 0.048969\ D_{1,t} + 0.022639\ D_{2,t} + 0.029878\ D_{3,t}\\ &\quad + 0.052110\ D_{4,t}, \quad t = 2, 3, \ldots, 734.\end{aligned} \tag{5.4}$$

In addition to the observed decline in the magnitude of slopes for the news variables, there is also a notable reduction in the impact of past prices on the non-trading hour price change. One might argue that the mean price change for non-trading hours is more minor, and thus, it is reasonable to conclude that the autocorrelation coefficients will also be smaller. However, this argument is flawed as the autocorrelation coefficient is independent of the magnitude of the values. A more compelling argument could be that presented by French & Roll (1986), which considers the different flow of private information during trading and non-trading hours, or that trading induces volatility on its own through mispricing.

Again, it is only the slope of variable $N^P_{t,c}$ that is significant in the case of variable N^P_t, with the same logical explanation supporting the correctness of this evaluation. However, this time, it is significant only at a 10 % significance level. Moreover, the slope for the $N^P_{t,c}$ in the FEM is now about 30 % lesser than in REM. We observe inconsistency when compared to the trading price change results. It might be caused by the specific behaviour of the non-trading price change, but also by the ‘Monday effect’, where all the news published through the weekend is assigned to Mondays $N^P_{t,c}$. Hence, the $N^P_{t,c}$ is often inflated, but the price changes are not.

Thus, the model might suppress the slope of this variable. In this estimated model, to influence the non-trading price change by half a percentage point, variable $N^P_{t,c}$ needs to take the value of 145, taking into account also the dual impact, since the variable $N^A_{t,c}$ is also statistically significant, or more than 460 for variable $N^P_{t-1,o}$. As mentioned in the previous subsection, those amounts of

	Estimated dependent variable:
	$\hat{\sigma}_{i,t,c}$
$\sigma_{i,t-1,o}$	0.113491***
	(0.014509)
$\sigma_{i,t-1,c}$	0.084640***
	(0.022971)
$N^P_{t,c}$	0.003115*
	(0.001675)
$N^P_{t-1,o}$	0.001074
	(0.000781)
$N^A_{t,c}$	0.000311**
	(0.000129)
$N^A_{t-1,o}$	0.000500
	(0.000322)
$D_{1,t}$	0.048969**
	(0.022712)
$D_{2,t}$	0.022639
	(0.029993)
$D_{3,t}$	0.029878
	(0.032403)
$D_{4,t}$	0.052110**
	(0.026231)
Observations	5,130
R^2	0.053323
Adjusted R^2	0.050360
F Statistic	28.799640*** (df = 10; 5113)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 5.4: Results of the FEM from the equation (4.8)

$N^P_{t,o}$ or $N^P_{t,c}$ are nonexistent or extremely rare in our dataset. Hence, we might conclude that the impact of this variable on the price change, however statistically significant, is negligible in the context of the close-to-open-hour price change. On average, the price change is inflated by 0.08 and 0.03 percentage points due to variables $N^P_{t,c}$ and $N^P_{t-1,o}$, respectively. Based on everything mentioned above about the variable N^P_t, we have to conclude that at a 5 % significance level, they are not significant in explaining the close-to-open price changes.

Regarding the variable N^A_t, this time, the $N^A_{t,c}$ is solely significant. That finally follows the intuition about the markets. The idea is that they adapt to any new information immediately. To influence the price change by 0.5 percentage points, the variable $N^A_{t,c}$ would have to take values more than 1600 and variable $N^A_{t-1,o}$ more than 970. Once again, these amounts were never achieved. Hence, we can conclude that although statistically significant, the N^A_t does not greatly impact the close-to-open price change.

The day-of-week effect remains the same as the results from REM. Tuesday and Friday differ at a 5 % significance level from Monday in the price change. That is concerning, as it differs from the phenomena we observed with the open-to-close price changes. This, again, can be caused by the different nature of the close-to-open and open-to-close share price changes.

In conclusion, our analysis revealed that $N^P_{t,o}$ significantly impacts price changes during trading hours, underscoring the influence of domestic political news on market behaviour. In contrast, N^M_t was confirmed to be insignificant in explaining price changes. We also found that price changes during trading hours exhibit no day-of-week effect. For non-trading hours, $N^P_{t,c}$ was not a significant factor in explaining price changes, though Tuesday and Friday showed significant differences from Monday. The N^P_t variable proved to have a greater impact on price changes than N^A_t. Additionally, we observed strong autocorrelation in price changes, suggesting a need for further investigation, potentially with a larger sample set, to better understand this phenomenon.

Chapter 6

Conclusion

This study investigates the impact of political news on price changes at the PSE by employing panel data and dynamic panel data methodologies, utilizing both random and fixed effects models. The endogenous nature of our variables posed a challenge; however, following the insights of Flannery & Hankins (2013), we determined that the FEM is most suitable for estimating both exogenous and endogenous variables.

The open-to-close hours' price changes were confirmed to be better explained by variable $N^P_{t,o}$ than the $N^A_{t,o}$ selection. The variable $N^P_{t,o}$ is statistically significant and meaningful in magnitude. Hence, we may say that politicians should try to stay out of newspaper headlines if they want the stock market to be less volatile.

This is also potentially valuable information for traders and investors at the PSE. If they expect higher amounts of political news to be published, there is a great chance that the market will be more volatile, giving them an opportunity to use this knowledge to their advantage and leverage it to make a profit.

Our analysis also reveals a significant distinction in the magnitude of slopes of lagged price changes between the close-to-open and open-to-close hours. The open-to-close hours seem to be more affected by past price changes. However, this result needs to be taken with caution, as even though the autocorrelation coefficients are significant at the 5% significance level, we could not estimate them unbiasedly and consistently.

Regarding the close-to-open price variance, there is room for further research, as we were able to explain just a small fraction of the price changes. The only meaningful factors we found were past price change values and the day-of-week effect, with Tuesdays and Fridays reporting higher price volatility than other days in the week. Although the $N_{t,c}^{A}$ variable was statistically significant, it was deemed unhelpful due to its inability to affect price change values meaningfully.

In conclusion, while this study provides significant insights into the relationship between political news and price changes at the PSE, it also highlights the need for further research. Expanding the dataset to include all shares traded at the PSE and employing alternative methodologies could provide a more comprehensive understanding of these dynamics. Our findings offer valuable implications for investors and policymakers alike, underscoring the influence of political news on market volatility and paving the way for future explorations in this domain.

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Appendix A

Appendix

Figures A.1, A.2, A.3 and A.4 concerns the endogeneity of our explanatory variables. Figures A.5, A.6 show the subsections of the ČTK's sections.

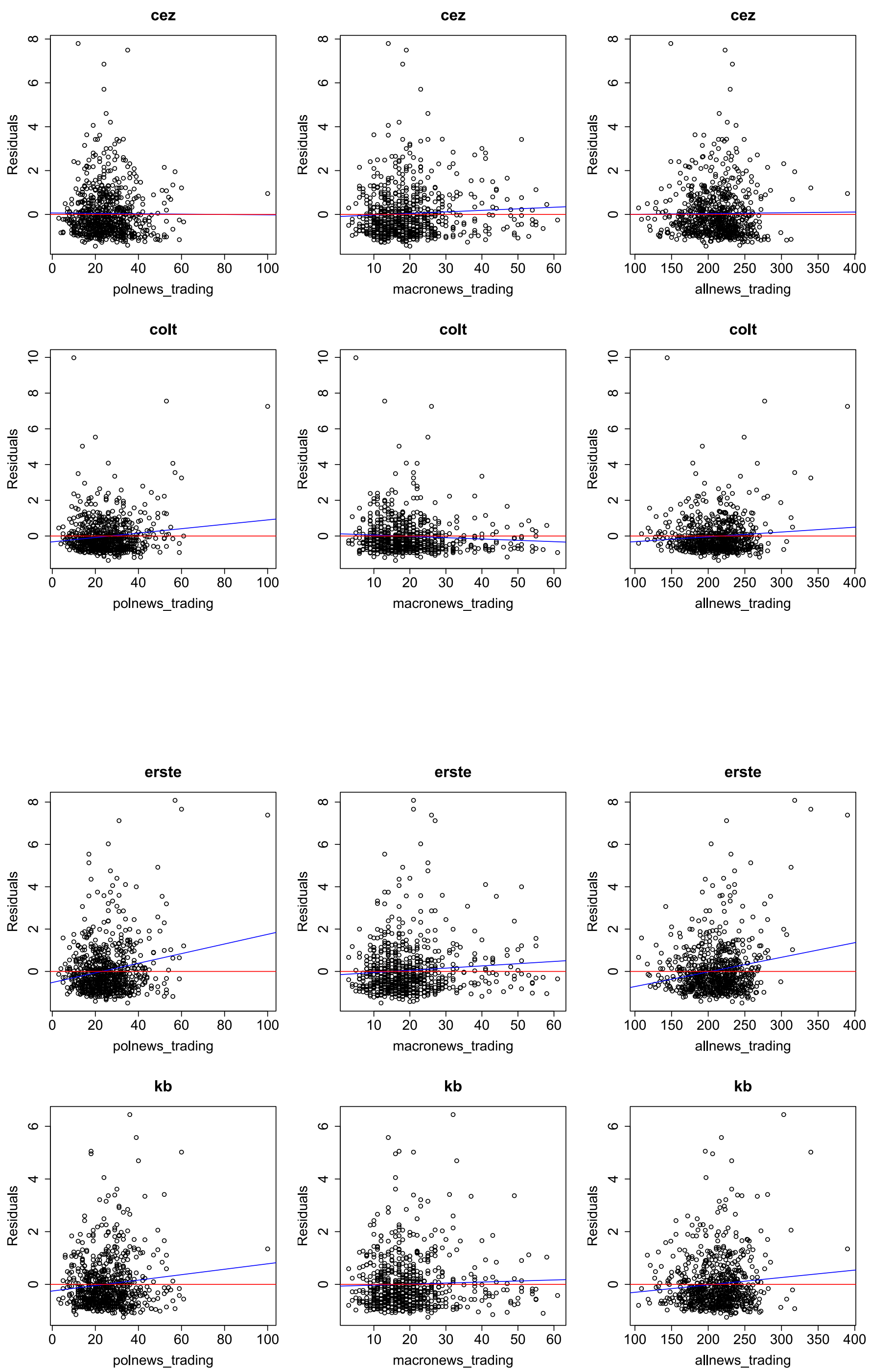

Figure A.1: Residuals vs Explanatory Variables from REM Model (4.4) a)

Residuals come from the REM following the model (4.4). Variable *polnews_trading* stands for $N^{P}_{t,o}$, similarly the other variables. The red line represents a zero mean trend, and variables uncorrelated with the error term should have a parallel trend line. The blue line represents the trend line.

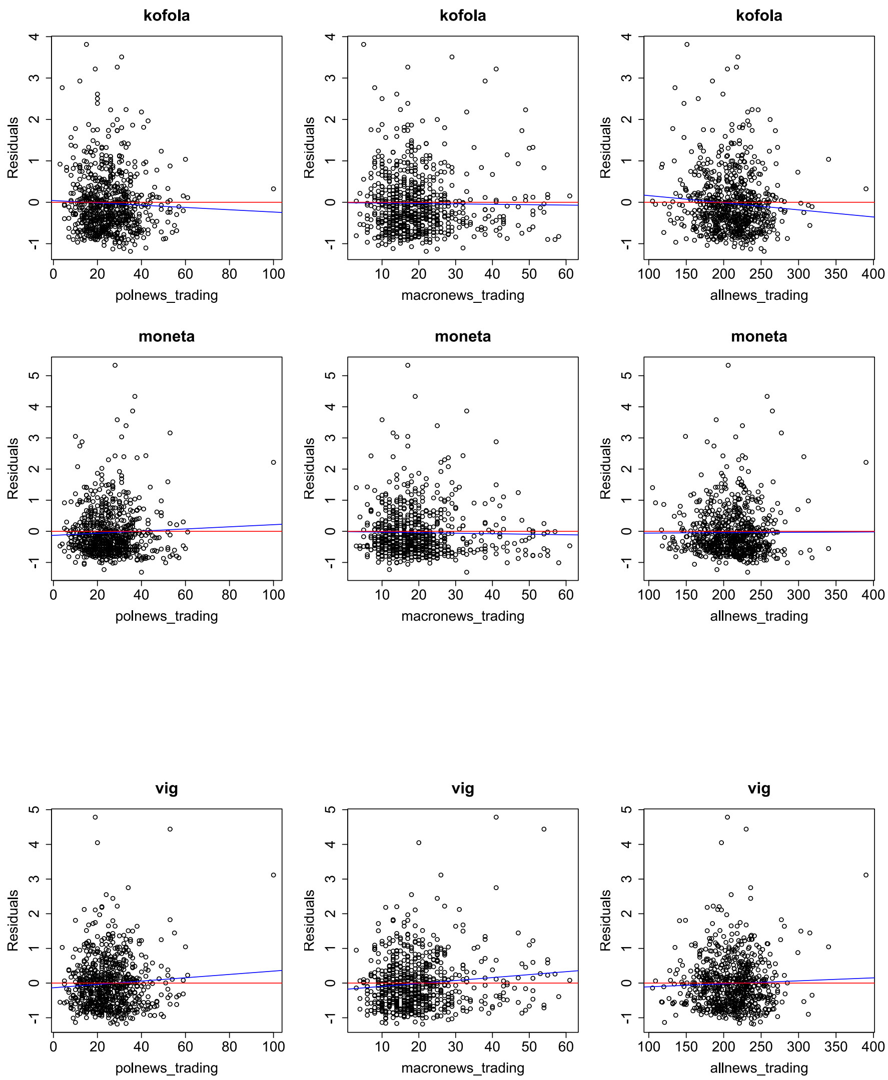

Figure A.2: Residuals vs Explanatory Variables from REM Model (4.4) b)

Residuals come from the REM following the model (4.4). Variable *polnews_trading* stands for $N^P_{t,o}$, similarly the other variables. The red line represents a zero mean trend, and variables uncorrelated with the error term should have a parallel trend line. The blue line represents the trend line.

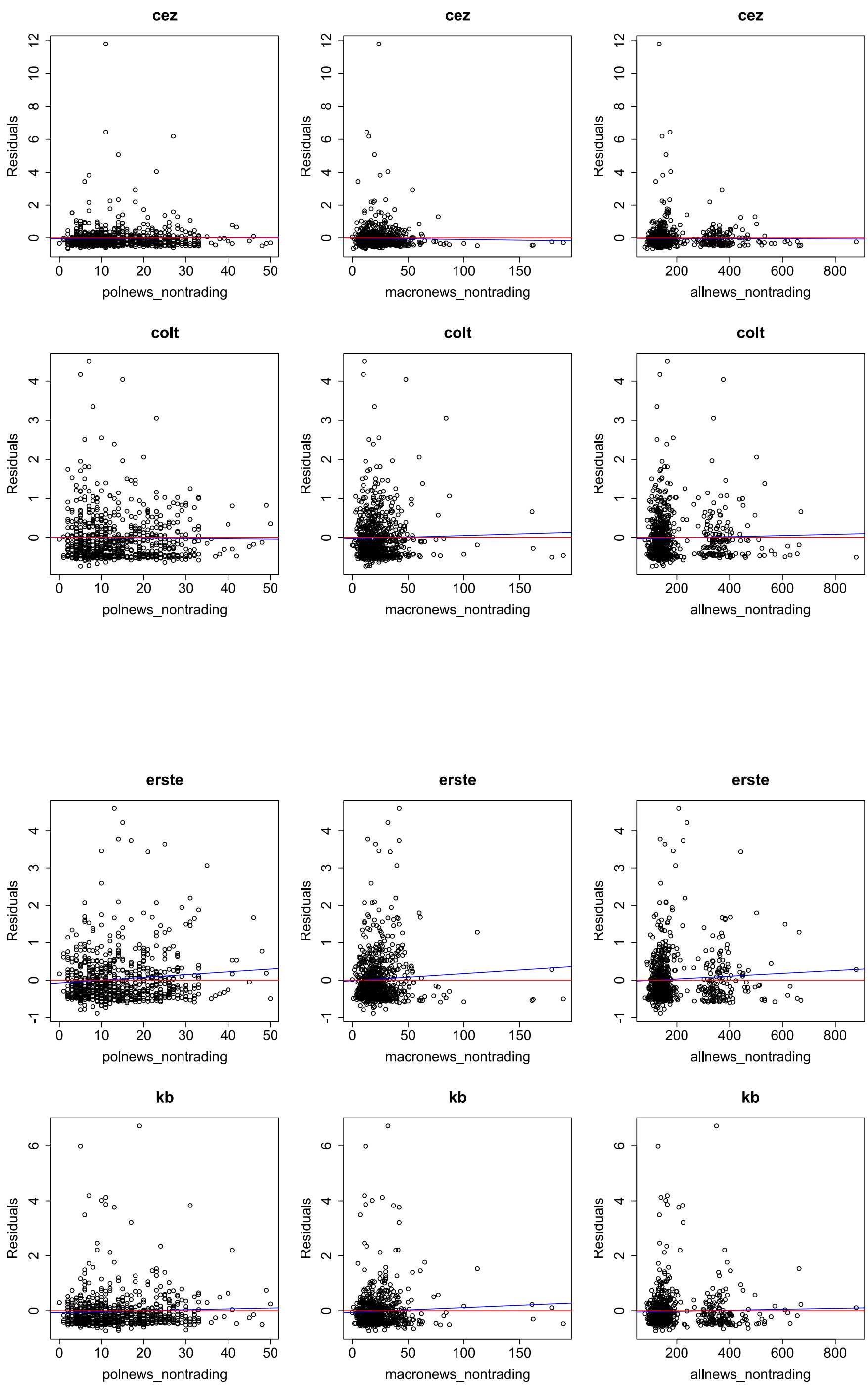

Figure A.3: Residuals vs Explanatory Variables from REM Model (4.5) a)

Residuals come from the REM following the model (4.5). Variable *polnews_nontrading* stands for $N^P_{t,c}$, similarly the other variables. The red line represents a zero mean trend, and variables uncorrelated with the error term should have a parallel trend line. The blue line represents the trend line.

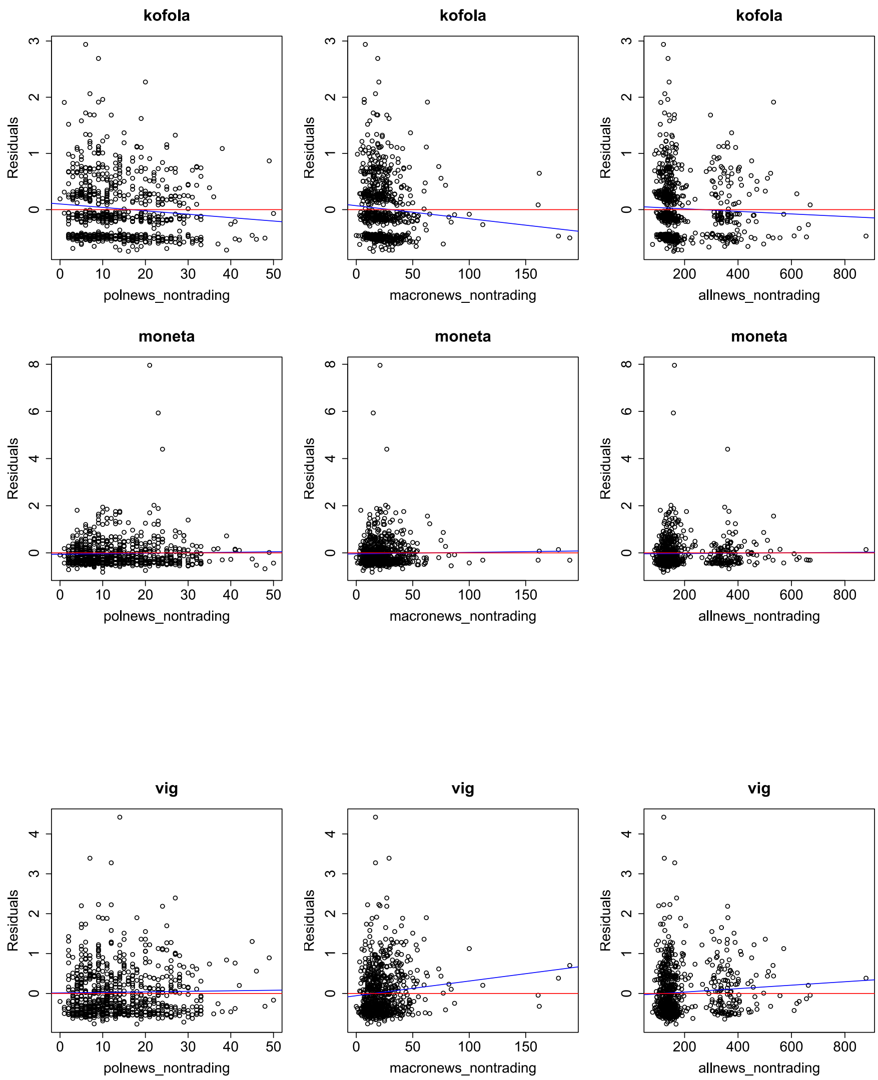

Figure A.4: Residuals vs Explanatory Variables from REM Model (4.5) b)

Residuals come from the REM following the model (4.5). Variable *polnews_nontrading* stands for $N^P_{t,c}$, similarly the other variables. The red line represents a zero mean trend, and variables uncorrelated with the error term should have a parallel trend line. The blue line represents the trend line.

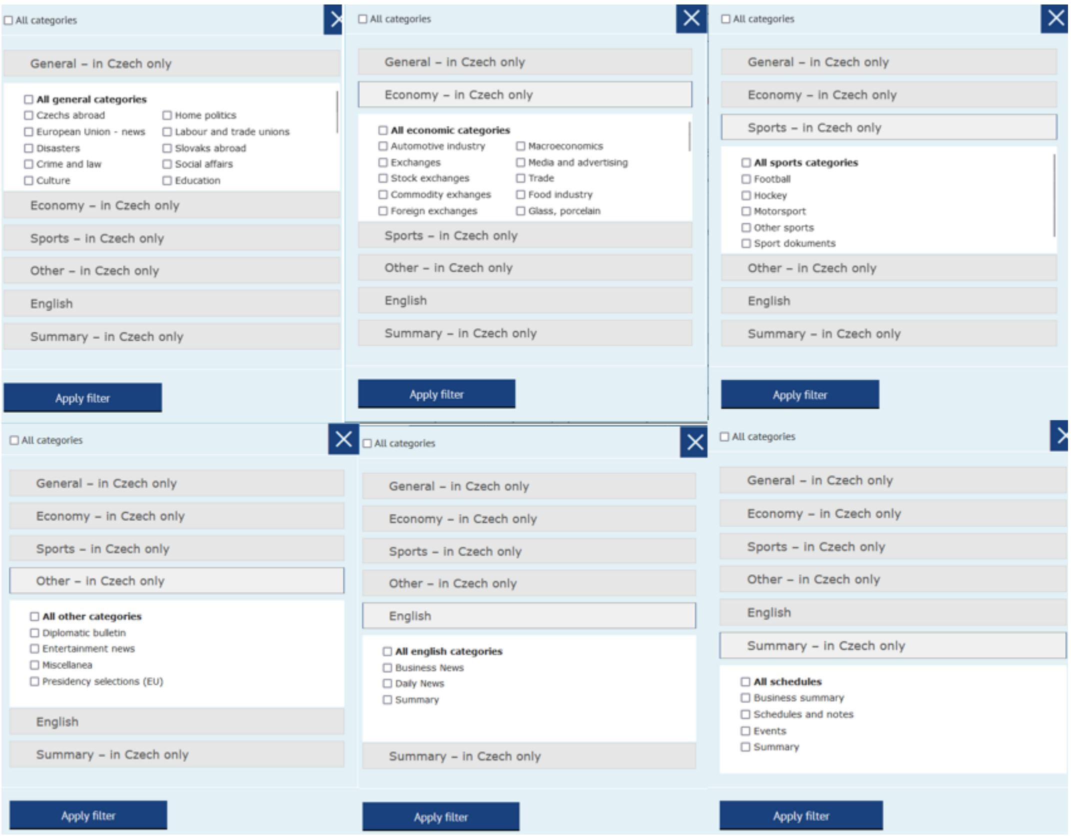

Figure A.5: Subsections of ČTK's Section 'Categories'

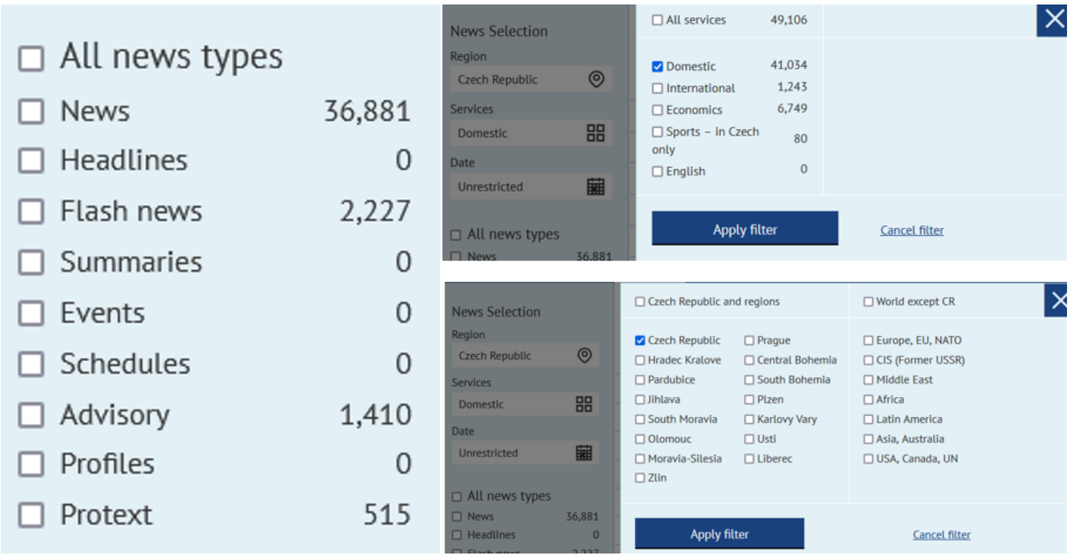

Figure A.6: Subsections of ČTK's Section 'News type', 'Region' and 'Services'

'News type' is located on the left, 'Region' in the top right and 'Services' in the bottom right.