Political and Institutional Aspects of Stock Return Dynamics

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Chapter 1

Introduction

The paramount importance of politics for financial markets comes into the spotlight of public interest in regular intervals. Unfortunately, this fervent interest has not been matched by academic research, and the substantial amount of literature advancing into the field has only begun to unveil the full dynamics political and institutional factors impose on international stock returns.

Hitherto dominant as a paradigm and one of the fundamentals of finance, the Efficient Market Hypothesis (EMH) states that, at any given time, asset prices on an informationally efficient market fully reflect all available information (Fama (1970)). Informational efficiency requires that markets absorb news instantaneously and that prices are solely driven by new relevant information. Moreover, a market is said to be efficient with respect to a specific information set if it is impossible to reap economic profits, i.e., risk-adjusted returns net of all costs, by trading on the basis of that information set (Jensen (1978), Malkiel (1992)). Important implications of this hypothesis are that, first, prices reflect the true value of any asset and contain all available information relevant for an investment decision and, second, investors cannot systematically earn abnormal profits.

The EMH has consistently been challenged by empiricists and a plethora of papers have documented long-term empirical regularities in returns that seem to contradict the concept of market efficiency. These phenomena have been referred to as anomalies because they cannot be explained within the paradigm of the EMH. Indeed, the study of stock market anomalies has been one of the most captivating and proliferating areas of financial market research during the last decades (for an overview see Singal (2004)). Prominently figure calendar anomalies such as the January effect (Rozeff and Kinney (1976), Reinganum (1983), Gultekin and Gultekin (1983)), the Monday effect (French

(1980), Jaffe, Westerfield, and Ma (1989)), and the turn-of-the-month effect (Ariel (1987), Lakonishok and Smidt (1988)) as well as the size effect (Banz (1981)) or the weather effect (Saunders (1993), Hirshleifer and Shumway (2003)). In an attempt to explain the puzzling persistence of these and other patterns despite existing arbitrage opportunities, a growing field of research called "Behavioral Finance" (Shleifer (2000), Shefrin (2002)) studies how cognitive or emotional biases create anomalies in market prices and returns that may be inexplicable via EMH alone.[1]

Recently, the literature on stock market anomalies has been appended by new and provocative empirical evidence on stock return patterns apparently induced by political variables. While the interdependence of politics and *economics* is comfortably established in the history of both disciplines and has produced such influential theories as the partisan theory (Hibbs (1977)) or the theory of political business cycles (Nordhaus (1975)), the linkage between politics and *finance* is less well-documented and the evidence on political stock market cycles scarce yet tendentiously debated. In particular, articles by Santa-Clara and Valkanov (2003) and Booth and Booth (2003) have galvanized the finance community and initiated vivid academic curiosity to dissect financial markets from a "political" angle. However, as of now the impact of political variables and events on global equity markets remains a widely open empirical question.

A crucial influence on market efficiency constitutes the degree of institutional trading in a stock. Different investor groups exhibit different trading behavior, and a whole body of literature is devoted to disentangling the effects of institutional trading (e.g., by pension or investment funds) as opposed to individual trading (by private investors) on stock markets. If stock returns exhibit exploitable regularities and institutional investors act as smart traders who exploit such patterns using their informational advantage, anomalies are supposed to disappear as the trading activities of this investor group arbitrage away systematic return patterns. If, on the other hand, institutional investors move market prices away from their fundamentally justified level due to strategic trading behavior, one could expect the anomaly to strengthen. The academic debate on whether institutional investors improve or impair market efficiency is far from being settled.

[1] The fields of Behavioral Finance and Behavioral Economics emerged in the late 1970s when psychologists began to benchmark their cognitive models of human judgment and decision-making under risk and uncertainty against economic models of rational behavior. The most influential article of that time, giving rise to a new research discipline, was by Kahneman and Tversky (1979). In recent years, the examination of behavioral aspects in finance and economics has gained momentum, culminating in Daniel Kahneman's 2002 Nobel laureate.

This thesis is driven by the motivation to overcome several shortcomings in the extant empirical finance literature by propounding and verifying a number of theoretical predictions. At this juncture, much work on the relation between political and institutional variables and financial markets lacks rigorous international investigation. The present thesis, therefore, accomplishes the task of "globalizing" an important line of research, filling in some voids in the international finance literature. Moreover, the sprouting field of behavioral finance is given fresh impetus since some of the examined issues could also be explained behaviorally. The body of this thesis consists of five self-contained essays, subsumed under three broader chapters. In detail, the following research questions are analyzed:

Chapter 2, titled "Political Cycles in Stock Market Returns", provides a thorough investigation into the behavior of stock market returns over political cycles. Prior research documented that U.S. stock prices tend to grow faster during Democratic than during Republican administrations (Santa-Clara and Valkanov (2003)) and to be boosted in the second half of the election cycle (Booth and Booth (2003)). Since these patterns cannot be explained by market fundamentals, the findings lend support to the existence of political stock market anomalies. However, the literature has barely looked beyond the U.S. and few other mature markets. Broadening of the available empirical evidence into an international dimension is crucial for several reasons: First, to warrant the status of global stock market anomalies alongside calendar or size effects, similar patterns should be observable in worldwide stock markets. Second, since political variables change rather infrequently, a look beyond the U.S. mitigates the data snooping bias and the risk of finding spurious relationships. For the sake of robustness, this chapter is further divided into two independent studies with different emphasis.

Section 2.1 investigates the Democrat premium (Santa-Clara and Valkanov (2003)) and the presidential cycle effect (Booth and Booth (2003)) in an international data set covering the most important world stock markets in terms of market capitalization. The cross-country approach facilitates the implementation of a panel framework, exploitable with more powerful econometric tools (see, e.g., Wooldridge (2001), Baltagi (2005)), in addition to an analysis of individual countries with different politico-institutional settings. The conclusive economic momentum of any findings will not retain certainty unless business cycle fluctuations are controlled for, tantamount to isolating the effects of political from macroeconomic variables which earlier studies have ascribed predictive power in forecasting stock returns (see, e.g., Fama (1991)). The results indicate that both deviations from market efficiency are not strikingly pervasive global phenomena and in the preponderance of countries do not hold.

Section 2.2 takes a slightly different perspective in examining whether stock returns elsewhere than in the U.S. also depend on the political orientation of the incumbents. Contradictory results of previous studies underline the sensitivity of estimates with regard to sample characteristics. Snowberg, Wolfers, and Zitzewitz (2007) analyze high-frequency data and claim that expected stock prices are actually higher under right-wing U.S. presidents—a finding in sharp contrast with Santa-Clara and Valkanov (2003). Nofsinger (2007) investigates the history of U.S. stock markets over a more extended time horizon and concludes that, in the long run, there is little support of any partisan premium. With this in mind, an additional examination is conducted in a broader set of countries, accounting also for higher frequency movements in stock prices around elections. Moreover, an event study unravels the question whether investment strategies based on governments' political slant and built around election dates are likely to yield profits. Results are not indicative of any systematic patterns or exploitable trading strategies.

Chapter 3, titled "Stock Market Volatility around National Elections", focusses on market dynamics around elections. Political events, and elections in particular, are a major influence on financial markets: "Markets tend to respond to new information regarding political decisions that may impact on a nation's fiscal and monetary policy. As such, political events are closely followed by investors who revise their expectations based on the outcome of these events. Among the many political events followed by market participants, political elections are particularly important because: 1. Elections provide voters (and investors) with an opportunity to influence the course of the medium- and long-term economic policies of a country. Voters choose whether to reelect incumbents based on their assessment of the states of candidates, parties, and the nation prior to the election. 2. Elections are events that attract the attention of media, pollsters, and political and financial analysts who filter information between politicians and the public. This process disseminates information to financial markets. 3. As the election outcome becomes more certain, financial market participants revise their prior probability distributions of policies to be implemented and the resulting economic effects" (Pantzalis, Stangeland, and Turtle (2000)). Evidence of sharp price movements in vote-casting periods will lend support to the conjecture that market participants tend to be surprised by the actual election outcome. However, many earlier electoral studies are plagued with the fact that elections are essentially rare events, thus providing scanty evidence to verify any theoretical predictions. Hence, the call for a comprehensive international study is evident.

Moreover, this chapter takes the analysis of political determinants of stock market behavior further from the first to the second moment of return distribution by modelling return volatility in a GARCH framework.[2] An event study then investigates whether elections induce higher stock market volatility. This is highly relevant for several reasons: First, the uncertainty about domestic election outcomes has important implications for the optimal portfolio strategies of risk-averse investors who tend to be insufficiently diversified on the international scale (French and Poterba (1991), Baxter and Jermann (1997)). Second, participants of the options markets have a powerful toolkit at hand to design lucrative volatility-based trading strategies. Finally, the results may be of interest to pollsters as they serve as an indirect evaluation of the quality of pre-election polls. In order to trace back any incidence of increased volatility around an election to its true source, an econometrically flawless isolation of the country-specific component of index return variance is imperative. We proceed along this path (Boehmer, Musumeci, and Poulsen (1991), Hilliard and Savickas (2002)) and find that the country-specific part of volatility increases dramatically in the vicinity of an election, which attests to the fact that investors are surprised by the ultimate election outcome. On top, factors that magnify the election-induced excess volatility are pinpointed.

In Chapter 4, titled "Institutional Investors and Stock Market Efficiency", the focus shifts from political to institutional determinants of stock return behavior. As such, this chapter combines two empirical studies investigating the effects of institutional trading on stock market anomalies in two of the Central and Eastern European emerging markets. Comprehensive changes in the Polish and Hungarian pension systems promote the exploration of this issue in a privileged setting. At the end of the 1990s, pension reforms took place in both countries and citizens were forced (in Poland) or allowed (in Hungary) to transfer part of their gross income to privately

[2] (G)ARCH-type models account for the fact that many financial and economic time series are characterized by time-varying volatility, more specifically, (generalized) autoregressive conditional heteroskedasticity, and allow for simultaneous estimation of mean and variance equations. ARCH processes (introduced by Engle (1982)) recognize the difference between unconditional and conditional variance allowing the latter to change over time as a function of past errors. GARCH processes (put forth by Bollerslev (1986)) provide a generalization in that they assume conditional variance to be a function of the past realizations of errors *and* past variances, thus facilitating a more parsimonious parameterization. Robert F. Engle was awarded the Nobel Prize in Economics 2003.

managed pension funds. These large funds entered the stock market and induced a considerable change in the investor composition on the Warsaw and Budapest Stock Exchanges. Markets that were first populated by a predominantly individual investor clientele changed to being dominated by institutional investors.

Section 4.1 investigates the impact of institutional investors on stock market efficiency by focussing on the January stock market anomaly. The January effect implies significantly higher returns in the first than in any other month (Rozeff and Kinney (1976), Gultekin and Gultekin (1983)), is often concentrated in the trading days after the turn of the year (Reinganum (1983)), and has been found to be attributable to two prominent explanations: tax-loss selling by individual investors and window-dressing by institutions. The Polish and Hungarian pension system reforms and the associated increase in investment activities of pension funds are used as a unique characteristic to, first, provide evidence on the impact of individual as opposed to institutional trading on the January seasonality and, second, test the above-mentioned explanations. The empirical results are favorable of the view that the increase in institutional ownership has reduced the magnitude of abnormally high January returns previously induced by individual investors' trading behavior.

In Section 4.2 the implications of payment patterns on the Monday effect (French (1980), Jaffe, Westerfield, and Ma (1989)) and the turn-of-the-month stock market anomaly (Ariel (1987), Lakonishok and Smidt (1988)) are subjected to scrutiny. Again, the special institutional setting the Polish and Hungarian stock markets provide is exploited, with their history encompassing periods of predominately individual and institutional trading. We find robust empirical evidence in favor of abnormally high stock returns on the first Mondays of the month and the trading days around the turn of the month. This pattern is consistent with the payment schemes in both countries and more pronounced during the period of individual trading relative to the period of increased institutional trading. Our findings are in line with Kamara (1997) and Chan, Leung, and Wang (2004) who find support for U.S. stock markets that an increase in institutional ownership has reduced the magnitude of the Monday anomaly.

The outlined research questions affect investors and academics alike: First, the results may help investors to better understand the mechanisms at work on global stock markets and to adjust their trading accordingly. The predictability of asset prices and, hence, the possibility to forecast the future development of prices of financial assets establishes a profit opportunity and is therefore of vital importance. Second, from an academic point of view, an examination of the dynamics of stock price behavior conditional upon political and institutional variables may contribute to our general understanding of stock market efficiency and inefficiencies.

Chapter 2

Political Cycles in Stock Market Returns

2.1 International Evidence on the Democrat Premium and the Presidential Cycle Effect[1]

2.1.1 Motivation

Recently, the studies by Santa-Clara and Valkanov (2003) as well as Booth and Booth (2003) have enriched the finance literature by providing new and provocative empirical evidence on two stock market anomalies. Although the nexus between asset markets and politics has not gone entirely unnoticed in the literature,[2] both investigations are the first to formally test the relationships and systematically examine their robustness. Santa-Clara and Valkanov (2003) find economically and statistically significant higher excess and real stock returns under U.S. Democratic presidencies than under Republican presidential administrations during the 1927–1998 period. This Democrat premium continues to hold after controlling for business cycle variables and time-varying risk premia.

Booth and Booth (2003) confirm the empirical finding of higher excess returns under Democratic presidents than under Republican presidents for a small stock portfolio, while large stock excess returns are not significantly different from each other

[1] This section is a revised version of an article published in the *North American Journal of Economics and Finance* (Bohl and Gottschalk (2006)).

[2] For example, Herbst and Slinkman (1984), Huang (1985), Stovall (1992), Gärtner and Wellershoff (1995), Hensel and Ziemba (1995), Johnson, Chittenden, and Jensen (1999), and Siegel (2002) document an empirical relationship between stock returns and politics in the U.S. Foerster and Schmitz (1997) examine the international pervasiveness of the U.S. election cycle and find robust empirical evidence in favor of a statistically significant relationship. For an overview of political effects on stock return dynamics, see also Bohl and Gottschalk (2005b).

during the 1926–1996 period. Moreover, U.S. stock excess returns are significantly higher in the last two years than in the first two years of the presidential term. This presidential cycle effect in stock excess returns cannot be explained by business condition proxies. Hence, the documented influences of the political cycle on stock returns in both investigations are puzzles and challenge the market efficiency hypothesis (Fama (1970)).

The findings outlined above raise the question whether the nexus between stock returns and politics holds beyond the U.S. Our investigation examines the hypothesis of a Democrat premium and a presidential cycle effect for 15 stock markets including the U.S. By broadening the evidence available in Santa-Clara and Valkanov (2003) and in Booth and Booth (2003) to an international dimension, we provide a comparison with the results contained in both studies and thereby reduce the data snooping bias. Using the above-mentioned authors' methodology, we are able to answer the question whether these anomalies exist not only in the U.S. but also in countries with different politico-institutional settings.[3] Furthermore, our data set allows us to investigate both anomalies in a panel framework. Compared to a separate investigation of individual countries, the use of a panel exploits a larger number of observations and increases the power of the statistical tests.

The remainder of this section is organized as follows. In Subsection 2.1.2 we outline the econometric approaches to investigate the above-mentioned anomalies, while Subsection 2.1.3 discusses the data. Subsection 2.1.4 contains the empirical results and Subsection 2.1.5 concludes.

2.1.2 Methodology

Our empirical analysis of the Democrat premium relies on the following regression equation:

$$r_{t+1} = \alpha_0 + \alpha_1 LW_t + \mathbf{c}'\mathbf{X}_t + u_{t+1}. \tag{2.1}$$

The dependent variable denotes the excess stock market return $r_{t+1} = r_{t+1}^{NOM} - i_{t+1}^{S}$, where r_{t+1}^{NOM} is the annualized nominal stock market return and i_{t+1}^{S} the short-term

[3] Scarce evidence in the existing literature suggests that this does not necessarily have to be the case. Hudson, Keasey, and Dempsey (1998) find marked reactions in the UK stock market around the election period but also note that the differences in returns under Tory and Labour governments are statistically insignificant. Cahan, Malone, Powell, and Choti (2005) report that New Zealand stock market returns were lower under left-leaning governments, which is in sharp contrast with the U.S. findings. Bohl and Gottschalk (2005a) and Döpke and Pierdzioch (2006) repudiate that German stock market returns tend to be higher during left-wing than during right-wing governments and that there is an inherent election cycle.

interest rate.[4] LW_t is a political dummy variable, $\mathbf{X}_t$ a vector of control variables, and u_{t+1} the error term, $u_{t+1} \sim N(0, \sigma^2)$. The political dummy variable LW_t takes on the value of 1 whenever a left-wing government is in office and 0 otherwise. The timing of the variables emphasizes that the political dummy variable is known at the start of the return period. Under the null hypothesis H_0: $\alpha_1 = 0$, the orientation of the government does not have an effect on stock returns. If the estimated parameter $\hat{\alpha}_1$ is statistically significant and positive (negative), then the evidence is favorable for a Democrat (Republican) premium. We maintain the terminology introduced by previous authors for the U.S. stock market and denote a left-wing premium as a Democrat premium and a right-wing premium as a Republican premium, referring to the U.S. party system.

In the compact depiction of Equation (2.1), a set of control variables X_{kt} is subsumed under the 6×1 vector $\mathbf{X}_t$, with $\mathbf{X}'_t = (X_{1t}, \ldots, X_{6t})$. $\mathbf{c}'$ denotes a 1×6 vector of parameters, $\mathbf{c}' = (c_1, \ldots, c_6)$. The omission of macroeconomic control variables related to the business cycle may lead to the misinterpretation of empirical findings because the effect of the political dummy variable on stock returns might merely be a reflection of business cycle fluctuations.[5] Specifically, the vector $\mathbf{X}_t$ includes:

1. the logarithm of the dividend yield DP_t;

2. the default spread DEF_t, which is defined as the difference between the return on a portfolio of corporate bonds and the return on long-term government bonds;

3. the term spread $TERM_t$, which is the difference between a long-term government bond yield and the short-term interest rate;

4. the relative interest rate $RREL_t$, which is defined as the deviation of the short-term interest rate from its one-year moving average; and

5. the expected inflation $E_t[INF_{t+1}]$, which we approximate by the future actual inflation rate.[6]

[4] Both variables are expressed in logarithms. This specification is the same as in Santa-Clara and Valkanov (2003) and makes our results directly comparable to theirs.

[5] Previous research has found GDP growth to be slower during Republican presidential mandates and inflation to be higher under Democratic administrations (see Alesina and Rosenthal (1995) and Alesina, Roubini, and Cohen (1997) for references).

[6] We thank Pierre Siklos for suggesting this additional control variable. Because expected inflation is generally unobservable by agents, previous studies have made diverse attempts to generate expected inflation proxies. For an early comparison of forecast models, see for example Fama and Gibbons (1984). An overview with related literature is also contained in Kolluri and Wahab (2008). In this study, we use actual future inflation as a measure of inflationary expectations. This simple proxy goes

6. the one-period lagged U.S. stock market return r_t^{US}.

The use of these conditioning variables is widely accepted. The literature on the predictability of stock market returns shows that the variables listed can explain significant variations in expected returns.[7] We rely on this empirical evidence to separate business cycle factors from political ones. We also include lagged U.S. stock market returns r_t^{US} to take into account the dependencies between the U.S. and other stock markets.

The presidential cycle effect is investigated in a similar manner by running the regression

$$r_{t+1} = \beta_0 + \beta_1 HALF_t + \mathbf{c}'\mathbf{X}_t + \upsilon_{t+1}, \tag{2.2}$$

where r_{t+1} denotes the excess stock market return over the short-term interest rate, $HALF_t$ the political dummy variable, and $\mathbf{X}_t$ the vector of control variables. The error term $\upsilon_{t+1} \sim N(0, \sigma^2)$. The political dummy variable $HALF_t$ is set to 1 in the second half of the government term and 0 otherwise.[8] The remaining notation is the same as above. We investigate the null hypothesis H_0: $\beta_1 = 0$. If the estimated parameter $\hat{\beta}_1$ is statistically significant and positive, then we have found evidence in favor of a presidential cycle effect. Again, we follow the terminology used by Booth and Booth (2003) and refer to the investigated phenomenon as the *presidential* cycle effect although we actually examine the link between stock returns and *government* cycles. In fact, most countries in our sample do not operate under a presidential system like the U.S. but under parliamentary or semi-presidential systems with a Premier or Prime Minister as the head of government and a President or Monarch as the—sometimes merely symbolic—head of state.

Equations (2.1) and (2.2) are estimated via Ordinary Least Squares (OLS). The standard errors are made robust to potential heteroskedasticity and autocorrelation in the residuals using the Newey and West (1987) method. The bandwidth for the

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beyond the traditional rational expectations premise in assuming the absence of shocks, i.e. a perfect foresight equilibrium. Since this chapter is ultimately concerned with the effects of political variables on stock market returns and relies on expected inflation merely as a control variable, we refrain from fitting more sophisticated inflation forecast models to the 15 countries in our sample, while aware that this might introduce a bias in our analysis.

[7] See, for example, Chen, Roll, and Ross (1986), Keim and Stambaugh (1986), Campbell and Shiller (1988), Fama and French (1988), Fama and French (1989), Campbell (1991), Chen (1991), Fama (1991), and Hodrick (1992).

[8] We have also used two other definitions of the political dummy variable. First, $HALF_t$ was set equal to 1 in the last 12 months of the government term and 0 throughout the rest of the election cycle. Second, following Alesina and Roubini (1992), a "threshold" approach was implemented, i.e., if elections were too close to previous elections (less than two years), they were not included in the tests. We report the findings of this robustness check below.

Newey-West approach has been set to 12 lags.[9] We estimate Equations (2.1) and (2.2) as country-by-country regressions and as panel regressions. The panel regression model applied is a fixed-effects model allowing for country-specific individual effects.[10] Transforming Equations (2.1) and (2.2) into this panel data model produces the following regression equations for the Democrat premium and the presidential cycle effect, respectively:

$$r_{i,t+1} = \alpha_{i,0} + \alpha_1 LW_{i,t} + \mathbf{c}'\mathbf{X}_{i,t} + u_{i,t+1}, \tag{2.3}$$

$$r_{i,t+1} = \beta_{i,0} + \beta_1 HALF_{i,t} + \mathbf{c}'\mathbf{X}_{i,t} + \upsilon_{i,t+1}, \tag{2.4}$$

where the subscript i denotes the cross-sectional dimension and t the time series dimension. Hence, $r_{i,t+1}$ is the stock market return in country i at time $t+1$. The explanatory variables are defined accordingly. $u_{i,t+1} \sim N(0, \sigma_u^2)$ and $\upsilon_{i,t+1} \sim N(0, \sigma_\upsilon^2)$. Equivalently to Equation (2.1), statistical significance and a positive (negative) sign of the estimated coefficient $\hat{\alpha}_1$ in Equation (2.3) is interpretable as evidence in favor of a Democrat (Republican) premium. As in Equation (2.2), a statistically significant and positive parameter estimate $\hat{\beta}_1$ in Equation (2.4) can be seen as evidence in favor of a presidential cycle effect in stock returns.

Equations (2.1) to (2.4) are estimated starting with the complete set of control variables outlined above. Next, we exclude step by step the variables with statistically insignificant coefficients at the 10% level. In the tables containing the empirical results for the 15 individual countries and the panel, we report (1) findings of the regressions including all control variables and (2) findings of the regressions including only control variables with statistically significant parameters at the 10% level.

2.1.3 Data

All time series data are of monthly frequency. In the majority of cases, the time series start in the period between 1957 and the early 1970s and end in 2004. The

[9] We have implemented a number of different bandwidth specifications for estimating Newey-West standard errors. Newey and West (1994) propose a "deterministic" rule which sets the number of lags as a fixed function of the sample length. Another class of lag selection methods includes the Akaike or Schwarz information criteria (Akaike (1974), Schwarz (1978)) or the general-to-specific methodology. The application of the suggested methods to our regression models usually yielded different lag lengths. Yet, the inclusion of 12 lags seemed to be a reasonable compromise, and our results are not sensitive to different bandwidth specifications.

[10] Other specifications of the model were considered, too. Among these were the inclusion of time-specific effects and the use of a variable-slopes and variable-intercepts model. In the end, we did not adopt these approaches to avoid a further loss of degrees of freedom. In addition, too many dummy variables may aggravate the problem of multicollinearity among regressors.

sample covers 15 developed stock markets: the U.S., Canada, Australia, New Zealand, Japan, and ten European countries (Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Sweden, and the UK).[11] The financial and economic time series are mostly taken from the International Financial Statistics (IFS) provided by the International Monetary Fund (IMF). The stock price indices contained in the International Financial Statistics database in general represent a broad market average. More detailed information on how these indices were constructed can be found in the Country Notes accompanying the printed version. The monthly stock returns have been annualized geometrically.[12]

The consumer price indices contained in the IFS are based on official statistics provided by the individual countries. The long-term interest rate is the yield on a 10-year government bond. As short-term interest rate we usually took the 3-month T-bill rate. However, for a number of countries we had to switch to alternative short-term interest rates (like the money market rate) because the otherwise exploitable sample length did not meet our requirements. Also, in some cases, the problem of too many missing values in some of the IFS time series had to be circumvented.

Dividend yields are taken from Thomson Financial Datastream. Default spreads were calculated from a corporate bond benchmark and a government bond benchmark also obtained from Thomson Financial Datastream. The term spread is the difference between the 10-year government bond yield and the 3-month T-bill rate. Table 2.1 contains information about the availability of the time series for all individual countries.

[Insert Table 2.1 here]

The data collected for the construction of the political dummy variables include election dates, dates of changes of governments, and the political orientation of all incumbent governments throughout the sample period. These data were mainly taken from Alesina and Roubini (1992), Johnson and Siklos (1996), Lane, McKay, and Newton (1997), Banks and Muller (1998), Pohl and Mayer (1998), Caramani (2000), and Müller and Strøm (2003). Various internet sources were also considered, especially for the more recent time periods.[13] Table 2.2 provides information about the number of

[11] Market capitalization of these countries accounts for over 80% of the global equity market (Bhattacharya and Daouk (2002)).

[12] The New Zealand stock price series was cleared of some outliers in 1998 that could not be confirmed when considering alternative data sources.

[13] In addition to the government web sites of the individual countries we consulted the following internet sources: `http://www.electionworld.org/`, `http://www.rulers.org/`, `http://www.terra.es/personal2/monolith/`, `http://dodgson.ucsd.edu/lij/`, `http://psephos.adam-carr.`

election cycles as well as the average, minimum, and maximum duration of election cycles in the 15 countries examined in this study. Moreover, the number of years when left-wing and right-wing administrations were in office are listed.

[Insert Table 2.2 here]

It should be noted that the classification of governments into left-wing and right-wing regimes and the identification of changes of political orientation of governments are not always as straightforward and unambiguous as in classical two-party systems like the U.S. or the UK. Some European countries indeed have a long tradition of center-right or center-left coalition governments, whose orientation can hardly be captured by a left-wing versus right-wing classification scheme without further differentiating. This is particularly true for Italy. Nevertheless, we tried to minimize the remaining ambiguities by assessing and consolidating the maximum range of information which was available to us. In case of doubt, we usually followed the conventions by Alesina and Roubini (1992), who obtained their classification of right-wing and left-wing governments from Alt (1985) and Banks and Muller (1998).

A further critical issue is the treatment of cases like the French *cohabitation*, which denotes a time period when the President and the Prime Minister in office belong to parties of different political orientation and, therefore, the political executive (exercised by the French President or the Prime Minister in their respective areas) is divided between a leftist and a rightist party. In this specific circumstance, we considered the political party of the Prime Minister as the relevant one.

2.1.4 Empirical Results

2.1.4.1 Democrat Premium

First, we estimate Equation (2.1) in order to investigate the Democrat premium for the 15 individual countries and the panel using excess stock returns. Results are shown in Table 2.3. The majority of the adjusted coefficients of determination $\overline{R}^2$ is of reasonable size, but the coefficients of the control variables do not in all cases have the theoretically expected sign. More importantly, however, the coefficients of the political dummy variable LW_t are statistically insignificant at the 10% level for 12 countries. By contrast, Denmark, Germany, and the U.S. show a left-wing premium.

net/, http://www.electionresources.org/, http://en.wikipedia.org/, and http://www.parties-and-elections.de/.

Comparable results are documented in Santa-Clara and Valkanov (2003) for the U.S. The evidence is robust concerning the selection of lags in the Newey-West approach[14] and the exclusion of statistically insignificant estimated coefficients. Moreover, the results of the panel regressions are not supportive of the hypothesis that the political orientation of the government exerts an influence on excess stock returns. The finding of a left-wing premium is rather an exception.

[Insert Table 2.3 here]

2.1.4.2 Presidential Cycle Effect

Next, we examine the empirical results of the presidential cycle effect reported in Table 2.4. When looking at the results for individual countries, in the majority of cases the findings are not supportive of a presidential cycle effect in excess stock returns. For 11 countries the coefficients for the political dummy variable $HALF_t$ are statistically insignificant. This finding is robust with respect to the selection of lags in the Newey-West approach (results are not reported but available on request) as well as the exclusion of insignificant coefficients of explanatory variables. There is some evidence that excess stock returns in Austria, Canada, the Netherlands, and New Zealand are higher in the second half of the government term compared to the first half. Nevertheless, the empirical findings for these countries are not robust across all specifications. These findings do not support the results documented in Booth and Booth (2003) for the U.S. Sweden, as an exception, exhibits significantly higher excess stock returns in the first half of the presidential term.

[Insert Table 2.4 here]

A closer look at the results of the panel regressions reveals that the parameters of the presidential cycle dummy variable $HALF_t$ do not have the theoretically expected sign and are statistically insignificant. Similar to the findings on the Democrat premium above, the international evidence is not favorable for the existence of a presidential cycle effect in excess stock returns.

[14] Results are not reported but available on request.

2.1.4.3 Robustness Checks

In addition to the findings reported in Tables 2.3 and 2.4 we performed a comprehensive robustness check. First, we re-estimated all regressions using *nominal* instead of *excess* stock market returns. Robust evidence in favor of a right-wing premium can be found only for Belgium, while for the remaining countries the parameters of the political variable are insignificant or show mixed results. With respect to the presidential cycle effect a similar picture emerges. Only for Austria, Canada, and Japan the political dummy variable is significant and positive. The evidence of the panel regressions is not favorable for a left-wing or right-wing premium and a presidential cycle effect. Hence, the findings relying on nominal stock returns do not change our conclusions on the existence of both political anomalies discussed above.

Second, the implementation of a threshold approach which excludes elections from the tests that are too close (less than two years) to previous elections did not affect our results at all. In contrast, the alternative specification of the presidential cycle dummy variable, where $HALF_t$ is set to 1 only in the last year of the government term, yielded slightly different results. With this definition of $HALF_t$, the presidential cycle effect detected in Canadian excess stock returns continues to hold. Furthermore, we now find a "reverse" presidential cycle effect with significantly higher returns in the first part of the government term in Italy. The other countries do not show any significant effects. Again, the panel investigation shows that a presidential cycle effect does not exist in the international data for either specification of the $HALF_t$ dummy variable.

Third, one might conjecture that potential differences in stock returns between left- and right-wing governments or between the first and the second half of the government term are driven by abnormally high or low returns around the election date.[15] In order to investigate this hypothesis we add another dummy variable to our regression models which is meant to capture such exceptional effects. This dummy takes on the value of 1 in an election month and 0 otherwise. However, our main results concerning the Democrat premium and the presidential cycle effect were unaffected. We therefore conclude that in countries with an apparent left-wing premium or presidential cycle effect, this pattern is not due to abnormal returns in the election month.

[15] We take into account the possibility that unpredicted events which are related to the election and are not captured in expected stock returns influence our empirical findings.

2.1.5 Summary and Conclusions

In this section, we provide new empirical findings on the Democrat premium and the presidential cycle effect by examining the implications of these hypotheses across 15 countries including the U.S. According to the Democrat premium hypothesis, stock returns are higher under left-wing than under right-wing administrations. The presidential cycle effect implies higher stock returns in the last half than in the first half of the government term. Since previous empirical evidence on either anomaly is limited to the U.S. (Santa-Clara and Valkanov (2003), Booth and Booth (2003)), we broaden the empirical findings on the nexus between stock markets and politics to an international dimension.

We find empirical evidence that both stock market anomalies are an exception rather than the rule. Out of the 15 countries under investigation, only the evidence for Denmark, Germany, and the U.S. is favorable for a left-wing premium. Similarly, supportive but non-robust evidence for a presidential cycle effect can be found only for Austria, Canada, and the Netherlands. More importantly, the empirical findings of the panel regressions do not bolster any of the two stock market anomalies. We therefore conclude that the Democrat premium and the presidential cycle effect are not strikingly pervasive global phenomena.

When interpreting our empirical results and comparing them with the findings for the U.S., some words of caution are in order, though. First, for many of the countries in our sample the classification into left-wing and right-wing governments is not as clear-cut as for the U.S. Second, we cannot completely rule out an influence on our empirical results from the fact that in the U.S. the President is both head of state and head of government, whereas in most of the countries under investigation a Prime Minister is heading the government without being, at the same time, head of state. Third, left-wing and right-wing governments alter fairly regularly in the U.S. By contrast, in most of the countries in our data set either left-wing or right-wing administrations dominate the sample.

2.1.6 Tables

Table 2.1: Data Availability

Country	Stock Price Index	Consumer Price Index	Long-Term Interest Rate	Short-Term Interest Rate	Dividend Yield	Default Spread	Term Spread
Australia	1958:01– 2004:07	1957:01– 2004:06	1957:01– 2004:07	1969:07– 2004:07	1973:01– 2004:10	1984:01– 2003:12	1969:07– 2004:07
Austria	1957:01– 1999:01	1957:01– 2004:07	1971:01– 2004:07	1967:01– 2004:07	1973:01– 2004:10	1999:01– 2003:12	1971:01– 2004:07
Belgium	1973:01– 2004:10	1957:01– 2004:07	1957:01– 2004:07	1957:01– 2004:07	1973:01– 2004:10	1984:01– 2003:12	1957:01– 2004:07
Canada	1957:01– 2004:07	1957:01– 2004:06	1957:01– 2004:07	1957:01– 2004:07	1973:01– 2004:10	1984:01– 2003:12	1957:01– 2004:07
Denmark	1957:01– 2000:12	1967:01– 2004:07	1960:01– 2004:07	1972:01– 2004:07	1973:01– 2004:10	1994:01– 2003:12	1972:01– 2004:07
France	1957:01– 2003:05	1957:01– 2004:06	1957:01– 2004:07	1970:01– 2002:09	1973:01– 2004:10	1984:01– 2003:12	1970:01– 2002:09
Germany	1970:01– 2004:07	1957:01– 2003:12	1957:01– 2004:07	1975:07– 2004:07	1973:01– 2004:10	1984:01– 2003:12	1975:07– 2004:07
Italy	1957:01– 2004:07	1957:01– 2004:07	1958:01– 2004:07	1977:03– 2004:07	1973:01– 2004:10	1984:01– 2003:12	1977:03– 2004:07
Japan	1957:01– 2004:06	1957:01– 2004:06	1966:10– 2004:02	1957:01– 2004:07	1973:01– 2004:10	1984:01– 2003:12	1966:10– 2004:02
Netherlands	1957:01– 2004:07	1957:01– 2004:07	1964:11– 2004:07	1960:01– 2004:07	1973:01– 2004:10	1984:01– 2003:12	1964:11– 2004:07
New Zealand	1961:01– 2004:07	1957:01– 2004:06	1964:01– 2004:07	1978:01– 2004:07	1988:01– 2004:10	N/A	1978:01– 2004:07
Norway	1957:01– 2001:08	1957:01– 2004:06	1961:09– 2004:07	1971:08– 2004:07	1980:01– 2004:10	N/A	1971:08– 2004:07
Sweden	1957:01– 2003:06	1957:01– 2004:07	1960:01– 2003:12	1960:03– 2001:12	1982:01– 2004:10	1984:01– 2003:12	1960:03– 2001:12
United Kingdom	1957:12– 1999:03	1957:01– 2004:07	1957:01– 2004:05	1964:01– 2004:05	1965:01– 2004:10	1984:01– 2003:12	1964:01– 2004:05
United States	1957:01– 2004:07	1957:01– 2004:07	1957:01– 2004:07	1957:01– 2004:07	1973:01– 2004:10	1984:01– 2003:12	1957:01– 2004:07

Note: The table provides an overview of the availability of financial and macroeconomic time series. The political variables (government and election cycle dummies) cover the period from 1957:01 to 2004:12 for all countries. The series present the maximum length of time series obtainable from either the IMF's International Financial Statistics (IFS) or Thomson Financial Datastream. The data sources are described in more detail in the text. "N/A" stands for "not available".

Table 2.2: Summary Statistics of Political Variables

	Election Cycle				Tenure	
Country	Number of Election Cycles	Average Duration	Minimum Duration	Maximum Duration	Left-Wing Govern-ment	Right-Wing Govern-ment
Australia	18	2.55	1.46	3.10	15.93	32.06
Austria	13	3.35	1.19	4.01	29.79	18.21
Belgium	14	3.21	1.67	4.16	8.19	39.80
Canada	15	3.14	0.74	4.93	32.27	15.70
Denmark	17	2.62	0.67	3.85	29.74	18.25
France	11	3.96	1.28	5.04	15.99	31.97
Germany	12	3.75	2.40	4.02	19.10	28.90
Italy[1]	11	3.91	1.98	5.06	10.94	36.03
Japan	15	3.03	0.71	3.99	1.53	46.37
Netherlands	13	3.37	0.69	4.65	14.49	33.50
New Zealand	15	2.98	2.63	3.20	17.28	30.72
Norway	11	3.99	3.93	4.01	30.27	17.73
Sweden	14	3.16	2.01	4.01	38.99	9.01
United Kingdom	11	3.79	0.61	5.06	18.52	29.48
United States	11	4.00	3.99	4.01	20.00	28.00
Panel	201	3.31	0.61	5.06	303.03	415.73

Note: This table presents aggregate information on the political variables used in this study. For each country, it reports the number of election cycles completed between 1957:01 and 2004:12 as well as their average, minimum, and maximum duration in years. Furthermore, the total number of years left-wing and right-wing administrations were in office is provided. [1] For Italy, columns 6 and 7 do not add up to 48 years because the 1993–1994 Ciampi administration was not attributed to any political camp. All other deviations are due to rounding.

Table 2.3: Regression Results on the Democrat Premium

Country	Regression Coefficients (t-Statistics)								$\overline{R}^2$	Sample
	$Const$	LW_t	DP_t	DEF_t	$TERM_t$	$RREL_t$	$E_t[INF_{t+1}]$	r_t^{US}		
Australia	−0.67	−0.18	−0.60	0.09	0.52	0.26	−3.59	0.14	0.24	1984:02–2003:12
	(1.72)*	(1.36)	(2.33)**	(0.16)	(1.87)*	(0.90)	(1.28)	(2.43)**		
	−1.16	−0.13	−0.36		0.96			0.17	0.13	1973:02–2004:07
	(4.27)***	(1.27)	(1.78)*		(4.24)***			(2.91)***		
Austria[1]	0.07	−0.90				−0.10	−10.83	0.15	0.03	1968:01–1999:01
	(0.09)	(1.22)				(0.18)	(3.25)***	(1.75)*		
	−0.35	−0.68					−12.02		0.03	1967:01–1999:01
	(0.64)	(1.23)					(3.89)***			
Belgium	−1.52	−0.19	0.23	1.28	1.55	−0.91	−11.29	0.20	0.26	1984:02–2003:12
	(5.05)***	(1.60)	(0.80)	(1.81)*	(7.01)***	(2.80)***	(2.19)**	(2.63)***		
	−1.31	−0.17		1.25	1.46	−0.72	−8.79	0.21	0.26	1984:02–2003:12
	(6.72)***	(1.42)		(1.87)*	(6.59)***	(2.41)**	(2.72)***	(2.89)***		
Canada	−1.41	0.07	−0.45	1.23	0.81	0.24	−3.86	0.08	0.39	1984:02–2003:12
	(4.79)***	(0.52)	(1.63)	(2.19)**	(3.45)***	(1.06)	(0.91)	(1.24)		
	−1.61	0.04	−0.53	1.41	1.05				0.39	1984:02–2003:12
	(5.60)***	(0.27)	(2.22)**	(2.74)***	(5.88)***					
Denmark[2]	−1.58	0.35	−0.48		0.67	0.11	−4.93	0.02	0.22	1973:02–2000:12
	(10.07)***	(2.64)***	(2.21)**		(3.75)***	(0.37)	(2.23)**	(0.38)		
	−1.61	0.35	−0.47		0.73		−5.37		0.22	1973:02–2000:12
	(12.20)***	(2.48)**	(2.08)**		(5.47)***		(2.57)**			
France	−1.81	0.19	0.70	−0.38	1.82	−0.16	−16.68	0.25	0.20	1984:02–2002:09
	(4.46)***	(1.18)	(1.26)	(0.30)	(5.17)***	(0.23)	(3.08)***	(1.73)*		
	−1.62	−0.09			1.32				0.00	1970:02–2002:09
	(4.41)***	(0.28)			(1.75)*					

(Continued)

Table 2.3 – Continued

Country	Regression Coefficients (t-Statistics)								$\overline{R}^2$	Sample
	$Const$	LW_t	DP_t	DEF_t	$TERM_t$	$RREL_t$	$E_t[INF_{t+1}]$	r_t^{US}		
Germany	−1.71	0.55	0.23	−2.08	1.61	0.04	−0.50	0.16	0.20	1984:02–2003:12
	(4.33)***	(2.52)**	(0.54)	(2.12)**	(3.85)***	(0.08)	(0.09)	(1.61)		
	−1.56	0.48		−1.82	1.70			0.17	0.21	1984:02–2003:12
	(8.69)***	(3.48)***		(2.17)**	(5.28)***			(2.07)**		
Italy	−0.65	0.26	−1.20	2.36	1.70	0.73	−0.52	0.28	0.21	1984:02–2003:12
	(1.26)	(1.05)	(2.75)***	(2.55)**	(2.88)***	(1.16)	(0.07)	(2.26)**		
	−0.56	0.26	−1.24	2.36	1.80			0.32	0.21	1984:02–2003:12
	(1.08)	(1.10)	(3.75)***	(2.45)**	(3.85)***			(3.17)***		
Japan	−0.14	−0.32	0.44	−0.53	1.02	0.09	−32.30	0.27	0.84	1984:02–2003:12
	(0.73)	(1.09)	(1.64)	(2.58)***	(18.13)***	(0.62)	(5.22)***	(2.87)***		
	−0.10	−0.30	0.46	−0.60	1.02		−32.26	0.29	0.84	1984:02–2003:12
	(0.53)	(0.98)	(1.68)*	(3.23)***	(18.78)***		(5.56)***	(3.10)***		
Netherlands	−0.58	−0.03	−0.47	0.40	1.34	0.14	−9.08	0.28	0.37	1984:02–2003:12
	(1.55)	(0.14)	(1.86)*	(0.44)	(4.57)***	(0.34)	(1.91)*	(4.84)***		
	−1.05	0.10			0.96		−6.10	0.33	0.41	1964:02–2004:07
	(11.07)***	(1.14)			(12.26)***		(3.32)***	(7.16)***		
New Zealand[3]	−1.19	−0.07	−0.18		1.46	0.77	−6.30	0.17	0.23	1988:02–2004:06
	(2.72)***	(0.45)	(0.60)		(2.51)**	(2.10)**	(1.04)	(2.08)**		
	−1.47	−0.15			1.58	0.56	−2.26	0.21	0.20	1978:02–2004:06
	(12.22)***	(1.25)			(4.46)***	(2.33)**	(1.99)**	(3.03)***		
Norway[3]	−0.17	0.48	−0.75		−0.33	0.59	0.97	0.53	−0.02	1980:02–2001:08
	(0.23)	(0.69)	(1.18)		(0.35)	(0.64)	(0.19)	(1.91)*		
	−0.84	0.33						0.46	−0.00	1971:08–2001:08
	(1.82)*	(0.67)						(1.82)*		

(Continued)

Table 2.3 – Continued

Country	Regression Coefficients (t-Statistics)								$\overline{R}^2$	Sample
	$Const$	LW_t	DP_t	DEF_t	$TERM_t$	$RREL_t$	$E_t[INF_{t+1}]$	r_t^{US}		
Sweden	−1.24	−0.20	0.68	−1.83	1.33	0.18	−11.89	0.23	0.17	1984:02–2001:12
	(3.26)***	(0.62)	(1.63)	(1.01)	(1.41)	(0.21)	(3.16)***	(1.64)*		
	−1.57	0.02	0.67		1.80		−8.13	0.31	0.15	1982:02–2001:12
	(3.60)***	(0.08)	(1.86)*		(2.77)***		(1.86)*	(2.39)**		
United Kingdom	−0.88	0.14	−0.36	−0.93	0.55	0.04	−3.94	0.19	0.24	1984:02–1999:03
	(1.62)	(0.93)	(0.83)	(0.81)	(2.55)**	(0.14)	(1.00)	(2.07)**		
	−1.09	0.31			1.06			0.60	0.06	1964:02–1999:03
	(3.31)***	(1.44)			(2.97)***			(2.69)***		
United States	−1.76	0.23	0.17	1.93	0.67	0.43	−4.99	0.20	0.51	1984:02–2003:12
	(4.14)***	(1.78)*	(0.97)	(2.83)***	(4.92)***	(1.36)	(1.21)	(3.17)***		
	−1.72	0.21		1.57	0.75	0.45		0.21	0.51	1984:02–2003:12
	(10.38)***	(3.01)***		(4.05)***	(5.72)***	(1.70)*		(3.12)***		
Panel		−0.84	0.16		0.81	−1.60	−4.75	0.85	0.00	1957:02–2004:12
		(0.94)	(0.35)		(2.20)**	(0.89)	(1.21)	(1.33)		
		−0.58						0.94	0.00	1957:02–2004:12
		(0.88)						(2.28)**		

Note: The model estimated is (2.1) $r_{t+1} = \alpha_0 + \alpha_1 LW_t + \mathbf{c}'\mathbf{X}_t + u_{t+1}$, where r_{t+1} denotes the log excess stock return and LW_t is a dummy variable taking on the value of 1 whenever a left-wing government is in office and 0 otherwise. $\mathbf{X}_t$ is a vector of control variables related to the business cycle and contains the dividend yield DP_t, the default spread DEF_t, the term spread $TERM_t$, the relative interest rate $RREL_t$, expected inflation $E_t[INF_{t+1}]$, and the lagged US return r_t^{US}. The values below the coefficients in parentheses represent Newey and West (Newey and West (1987)) serial correlation and heteroskedasticity robust t-statistics. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively. In the panel regressions country-specific intercepts are not reported.

[1] For Austria, DP_t, DEF_t, and $TERM_t$ were omitted in the country regressions in order to increase the sample length. Otherwise, the sample would not cover any right-wing governments.

[2] For Denmark, DEF_t was omitted in order to increase the sample length. Otherwise, the sample would not cover any right-wing governments.

[3] For New Zealand and Norway, default spreads DEF_t were omitted in the country regressions due to data unavailability. For the same reason, DEF_t was not included in the panel regressions either.

Table 2.4: Regression Results on the Presidential Cycle Effect

Country	Regression Coefficients (t-Statistics)								$\overline{R}^2$	Sample
	$Const$	$HALF_t$	DP_t	DEF_t	$TERM_t$	$RREL_t$	$E_t[INF_{t+1}]$	r_t^{US}		
Australia	−0.40	−0.01	−0.80	0.36	0.30	0.22	−5.91	0.15	0.23	1984:02–2003:12
	(1.49)	(0.08)	(4.51)***	(0.65)	(1.28)	(0.69)	(3.05)***	(2.61)***		
	−1.22	0.11	−0.41		1.03			0.18	0.12	1973:02–2004:07
	(4.28)***	(1.38)	(1.96)**		(4.12)***			(3.35)***		
Austria[1]	−0.88	0.39				−0.60	−12.27	0.17	0.02	1968:01–1999:01
	(4.31)***	(1.89)*				(1.08)	(3.94)***	(1.94)*		
	−1.08	0.31					−12.76		0.02	1967:01–1999:01
	(7.13)***	(1.61)					(4.19)***			
Belgium	−1.49	−0.01	0.19	0.93	1.38	−0.73	−11.91	0.17	0.25	1984:02–2003:12
	(4.66)***	(0.10)	(0.62)	(1.52)	(6.35)***	(2.19)**	(2.35)**	(2.30)**		
	−1.47	−0.06			1.39		−3.84	0.15	0.26	1973:02–2004:07
	(9.20)***	(0.69)			(6.69)***		(1.71)*	(2.76)***		
Canada	−1.38	0.12	−0.50	1.31	0.80	0.19	−4.79	0.07	0.39	1984:02–2003:12
	(6.77)***	(1.67)*	(2.10)**	(2.43)**	(3.44)***	(0.79)	(1.09)	(1.12)		
	−1.59	0.11	−0.59	1.39	1.03				0.39	1984:02–2003:12
	(7.79)***	(1.49)	(3.41)***	(2.98)***	(6.48)***					
Denmark[2]	−1.45	0.11	−0.36		0.83	0.03	−5.26	0.06	0.19	1973:02–2000:12
	(7.22)***	(0.94)	(1.55)		(3.66)***	(0.09)	(2.22)**	(0.87)		
	−1.55	0.07			0.86		−8.21		0.15	1972:02–2000:12
	(9.52)***	(0.50)			(4.29)***		(4.61)***			
France	−1.56	0.08	0.55	−0.95	1.74	−0.30	−14.71	0.25	0.20	1984:02–2002:09
	(3.10)***	(0.53)	(0.84)	(0.76)	(4.32)***	(0.44)	(2.41)**	(1.71)*		
	−1.48	−0.37			1.42				0.00	1970:02–2002:09
	(3.99)***	(1.20)			(2.10)**					

(Continued)

Table 2.4 – Continued

	Regression Coefficients (t-Statistics)									
Country	$Const$	$HALF_t$	DP_t	DEF_t	$TERM_t$	$RREL_t$	$E_t[INF_{t+1}]$	r_t^{US}	$\overline{R}^2$	Sample
Germany	−1.58	0.22	0.09	0.05	2.01	−0.02	−2.05	0.24	0.19	1984:02–2003:12
	(3.83)***	(1.47)	(0.22)	(0.07)	(5.07)***	(0.03)	(0.33)	(2.38)**		
	−1.35	0.09	−0.31		1.88			0.19	0.25	1975:08–2004:07
	(6.75)***	(0.91)	(1.75)*		(8.22)***			(2.62)***		
Italy	−0.37	−0.02	−1.26	2.23	1.45	0.73	−0.61	0.26	0.21	1984:02–2003:12
	(0.89)	(0.12)	(3.02)***	(2.42)**	(2.72)***	(1.08)	(0.09)	(2.02)**		
	−0.28	−0.03	−1.31	2.23	1.56			0.30	0.21	1984:02–2003:12
	(0.66)	(0.19)	(4.27)***	(2.31)**	(3.72)***			(2.77)***		
Japan	−0.27	0.09	0.42	−0.49	1.04	0.05	−28.85	0.27	0.84	1984:02–2003:12
	(1.22)	(0.69)	(1.66)*	(2.13)**	(17.68)***	(0.41)	(4.59)***	(2.88)***		
	−0.25	0.10	0.44	−0.52	1.05		−28.93	0.28	0.84	1984:02–2003:12
	(1.16)	(0.70)	(1.68)*	(2.57)**	(17.71)***		(4.72)***	(2.97)***		
Netherlands	−0.71	0.20	−0.41	−0.10	1.35	0.16	−9.87	0.29	0.38	1984:02–2003:12
	(2.01)**	(2.29)**	(2.09)**	(0.11)	(6.23)***	(0.45)	(2.56)**	(5.33)***		
	−0.82	0.08	−0.27		0.99		−4.75	0.28	0.40	1973:02–2004:07
	(4.24)***	(1.03)	(1.92)*		(9.02)***		(2.13)**	(6.65)***		
New Zealand[3]	−1.26	0.06	−0.16		1.37	0.78	−7.58	0.16	0.24	1988:02–2004:06
	(2.96)***	(0.56)	(0.55)		(2.91)***	(2.16)**	(1.82)*	(2.30)**		
	−1.67	0.20			1.68	0.59	−2.30	0.19	0.21	1978:02–2004:06
	(17.84)***	(2.08)**			(3.93)***	(2.74)***	(2.48)**	(3.04)***		
Norway[3]	0.67	−1.02	−0.91		−0.65	1.41	0.64	0.44	−0.01	1980:02–2001:08
	(0.41)	(1.21)	(1.14)		(0.57)	(1.46)	(0.14)	(1.54)		
	−0.25	−0.63						0.48	−0.00	1971:08–2001:08
	(0.24)	(0.98)						(1.66)*		

(Continued)

Table 2.4 – Continued

Country	Regression Coefficients (t-Statistics)								$\overline{R}^2$	Sample
	$Const$	$HALF_t$	DP_t	DEF_t	$TERM_t$	$RREL_t$	$E_t[INF_{t+1}]$	r_t^{US}		
Sweden	−1.28	−0.13	0.65	−1.70	1.18	0.33	−11.92	0.24	0.17	1984:02–2001:12
	(3.50)***	(0.76)	(1.53)	(1.11)	(1.22)	(0.40)	(2.73)***	(1.78)*		
	−1.36	−0.18			1.23			0.24	0.13	1960:04–2001:12
	(8.98)***	(1.66)*			(6.16)***			(3.53)***		
United Kingdom	−0.58	−0.02	−0.52	−1.02	0.45	0.07	−4.33	0.19	0.23	1984:02–1999:03
	(1.66)*	(0.18)	(1.56)	(0.71)	(2.03)**	(0.23)	(1.01)	(2.06)**		
	−0.89	−0.27			1.19			0.59	0.05	1984:02–1999:03
	(1.97)**	(1.37)			(2.69)***			(2.82)***		
United States	−1.32	0.05	0.03	1.52	0.64	0.12	−9.39	0.22	0.51	1984:02–2003:12
	(5.74)***	(0.79)	(0.19)	(2.60)***	(4.17)***	(0.60)	(2.53)**	(4.33)***		
	−1.31	0.05		1.49	0.67		−8.98	0.22	0.51	1984:02–2003:12
	(7.17)***	(0.73)		(3.74)***	(5.17)***		(2.45)**	(4.41)***		
Panel		−0.82	0.29		0.73	−1.41	−6.63	0.83	0.00	1957:02–2004:12
		(1.12)	(0.49)		(1.63)	(0.87)	(1.20)	(1.34)		
		−0.70					−18.72		0.00	1957:02–2004:12
		(1.20)					(2.31)**			

Note: The model estimated is (2.2) $r_{t+1} = \beta_0 + \beta_1 HALF_t + \mathbf{c}'\mathbf{X}_t + \upsilon_{t+1}$, where r_{t+1} denotes the log excess stock return and $HALF_t$ is a dummy variable taking on the value of 1 in the second half of the government term and 0 otherwise. $\mathbf{X}_t$ is a vector of control variables related to the business cycle and contains the dividend yield DP_t, the default spread DEF_t, the term spread $TERM_t$, the relative interest rate $RREL_t$, expected inflation $E_t[INF_{t+1}]$, and the lagged US return r_t^{US}. The values below the coefficients in parentheses represent Newey and West (Newey and West (1987)) serial correlation and heteroskedasticity robust t-statistics. *, **, *** denote statistical significance at the 10%, 5%, and 1% level, respectively. In the panel regressions country-specific intercepts are not reported.

[1] For Austria, DP_t, DEF_t, and $TERM_t$ were omitted in the country regressions in order to increase the sample length.

[2] For Denmark, DEF_t was omitted in order to increase the sample length.

[3] For New Zealand and Norway, default spreads DEF_t were omitted in the country regressions due to data unavailability. For the same reason, DEF_t was not included in the panel regressions either.

2.2 Political Orientation of Government and Stock Market Returns[16]

2.2.1 Motivation

An important question faced by every voter on Election Day is which of the parties is best equipped to foster the development of economy and capital markets. In the pursuit of their own political agenda, the winning party or coalition can fine-tune fiscal policy and significantly impact future economic outcomes. Depending on their political orientation, the objectives of different political camps can be quite disparate. As suggested by the partisan theory of Hibbs (1977), left-wing governments tend to cater for the well-being of their working class electorate by targeting unemployment. Right-wing governments, on the other hand, prioritize reduction in inflation feared by higher income and occupational status groups.[17]

Several earlier papers focussed specifically on the relationship between the political orientation of the executive branch of government and stock market performance. Johnson, Chittenden, and Jensen (1999) and Santa-Clara and Valkanov (2003) report that U.S. stock market returns were higher under Democratic than Republican presidencies, with the difference being particularly large for small-stock portfolios. This anomaly cannot be explained away by variations in business cycle proxies. Huang (1985) and Hensel and Ziemba (1995) look at whether presidential trading strategies are able to improve investors' risk-return trade-off.

From an international investor's perspective, it would be interesting to know whether the conclusions obtained from the U.S. data can be generalized to accommodate a global context.[18] The existing literature offers some indications that this does not necessarily have to be the case. Hudson, Keasey, and Dempsey (1998) find marked reactions in the UK stock market around the election period but also note that the differences in returns under Tory and Labour governments are statistically insignificant. Cahan, Malone, Powell, and Choti (2005) report that New Zealand stock market returns were lower under left-leaning governments, which is in sharp contrast

[16] This section is a revised version of an article published in the *Applied Financial Economics Letters* (Białkowski, Gottschalk, and Wisniewski (2007)).

[17] The nexus between inflation and asset prices has been established in Al-Khazali and Pyun (2004) and Maghyereh (2006).

[18] Papers that have established profitable trading strategies for the U.S. are Umstead (1977), Riley and Luksetich (1980), and Gärtner and Wellershoff (1995). Bohl, Döpke, and Pierdzioch (2008) question these findings.

with the U.S. findings. Our investigation adds to the presidential puzzle literature by extending the empirical analysis beyond a single stock market. The data set compiled for this study covers 24 OECD countries and 173 different governments. Since elections are relatively infrequent, a multi-country approach allows increasing the number of observations and the power of statistical tests.

The remainder of this section is organized as follows. Subsection 2.2.2 describes data sources and sample characteristics, while Subsection 2.2.3 briefly outlines the econometric methods applied. Subsection 2.2.4 investigates the behavior of stock market indices around Election Day and throughout the tenure of different administrations. The implications for investors and conclusions are contained in Subsection 2.2.5.

2.2.2 Data

In order to investigate the nexus between political variables and stock returns, the author attempted to construct a comprehensive data set including all OECD countries. Regrettably, Iceland, Ireland, Luxembourg, Slovakia, South Korea, and Switzerland had to be excluded from the analysis because either Morgan Stanley Capital International Inc. (MSCI) did not provide data on stock market indices for these capital markets or there was not a single change in the orientation of the government throughout the period for which the index was available. The returns for the remaining 24 countries[19] were computed using the U.S. dollar denominated, value-weighted, and dividend-adjusted MSCI Country Indices spanning a period from January 1980 through December 2005. Whenever daily data on the MSCI index was not available from January 1980, the sample period was adjusted accordingly. The stock market data were sourced from Thomson Financial Datastream.

The prevailing political system in a given country (presidential or parliamentary) determines the relevant type of election that will be examined. Election dates as well as the exact start and end dates of each government's term in office were obtained from Lane, McKay, and Newton (1997), Laver and Schofield (1998), Caramani (2000), Müller and Strøm (2003), and Banks, Muller, and Overstreet (2004). The classification of governments into left- and right-leaning administrations was taken from Alt (1985), Alesina and Roubini (1992), and Banks, Muller, and Overstreet (2004). Coalition governments were attributed to the political camp they are conventionally associated

[19] This results in 19 developed markets (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, UK, U.S.) and 5 emerging markets (Czech Republic, Hungary, Mexico, Poland, Turkey).

with. Table 2.5 describes the characteristics of the political and financial variables used in this study.

[Insert Table 2.5 here]

Over 60% of the countries had daily MSCI index data available from January 1980, whereas in the remaining cases the index starts at a later date. Among the 24 nations, Denmark and Australia had the highest number of governments included and Greece had the lowest due to short index availability. The data set covers a comparable number of 85 left-wing and 88 right-wing governments. Although the number of right-wing cabinets was slightly higher, the left-wing governments had tenures that were on average 70 days longer. This translates into a longer overall term in office for the left camp.

2.2.3 Methodology

This study quantifies the effect of government orientation on stock market returns, both around and in-between elections. First, in order to analyze return dynamics around the election date, a simple event study is conducted (see, e.g., Campbell, Lo, and MacKinlay (1997) or Wilkens and Wimschulte (2005)).[20] The event day is defined as the Election Day or, for those instances when elections took place during the weekend or on a bank holiday, the trading day thereafter. For the purpose of comparison, two sets of events are considered: left-wing electoral victories ("L wins") and right-wing triumphs ("R wins"). Conventions in the related literature motivate the set up of $T = 250$ days for the estimation and calibration period, while the event window spans 51 days and is centered around the election (day zero).

To estimate the election's impact in any of the two cases, we first require a measure of *normal* stock market performance, i.e., returns to be expected without the election event. *Abnormal returns* can then be computed by subtracting *expected returns* $E(r_{i,t})$ from *actual returns* $r_{i,t}$. In the context of this study, a *market-adjusted*

[20] Event studies were first introduced to economics by the seminal studies of Ball and Brown (1968) and Fama, Fisher, Jensen, and Roll (1969) and have been widely used as a methodological tool since then. For overview articles see, e.g., MacKinlay (1997) or Binder (1998). Brown and Warner (1980), for monthly data, and Brown and Warner (1985), for daily data, are useful papers that discuss several methodological improvements since the pioneering studies and consider practical implementation issues.

model is adopted and abnormal returns $AR_{i,t}$ relative to the benchmark are derived as follows:

$$AR_{i,t} = r_{i,t} - E(r_{i,t}) = r_{i,t} - \frac{1}{T}\sum_{s=1}^{T} r_{M,s}. \tag{2.5}$$

$r_{i,t}$ and $r_{M,s}$ are the continuously compounded returns of country index i and the world index, respectively, over a one-day period. The subtrahend in Equation (2.5) represents our measure of normal stock market performance: the arithmetic average of market returns over the length of the estimation window (T days).[21]

The abnormal returns $AR_{i,t}$ are subsequently averaged across all N relevant events to yield the *average abnormal return* at time t:

$$AR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}. \tag{2.7}$$

The average abnormal returns AR_t are then cumulated over the period (t_1, t_2) in order to produce an estimate of the *cumulative average abnormal return* during the event window:

$$CAR_{t_1,t_2} = \sum_{t=t_1}^{t_2} \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}. \tag{2.8}$$

The statistical significance of CAR_{t_1,t_2} is evaluated using the following standard test statistic (Brown and Warner (1985)):

$$t^{B/W}_{CAR_{t_1,t_2}} = \frac{CAR_{t_1,t_2}}{\hat{\sigma}(AR_t)\sqrt{t_2 - t_1 + 1}}, \tag{2.9}$$

where CAR_{t_1,t_2} is the cumulative average abnormal return over the event window (t_1, t_2) and $\hat{\sigma}(AR_t)$ is the estimated standard deviation of the average abnormal returns AR_t computed in the time-series dimension. Under the null hypothesis, the test statistic in Equation (2.9) follows a t-distribution with 249 degrees of freedom (see Brown and Warner (1985)). For sufficiently large calibration periods, the Student-t distribution can be approximated sufficiently accurately by a standard normal distribution.

[21] The results of the event study and their validity will depend substantially on the appropriateness of the assumed return model. For the sake of robustness, we also implement a *market model* (Sharpe (1963)) as the relevant benchmark:

$$AR_{i,t} = r_{i,t} - E(r_{i,t}) = r_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i r_{M,t}), \tag{2.6}$$

where $AR_{i,t}$ and $r_{i,t}$ are as previously labelled, $r_{M,t}$ denotes the return of the market portfolio, and $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the parameter estimates of the market model. Results are not reported since they were very similar to the above specification.

Next, we take a closer look at average stock market returns over the entire term of leftist and rightist governments. For either political camp in each particular country, daily returns are annualized according to the following formula:

$$(\sum_{i=1}^{GovDays} r_i)/(\frac{GovDays}{TradeDays}), \tag{2.10}$$

where r_i denotes the daily stock market return, $GovDays$ corresponds to the total number of days left-wing (right-wing) governments were in office and $TradeDays$ to the number of trading days. A bootstrap test (Efron (1979)) based on 1,000 replications is then used to determine whether the difference between mean annual returns under left-wing and right-wing governments is statistically significant.

2.2.4 Results

2.2.4.1 Abnormal Returns around Election Day

One of the features of political systems is that elections do not necessarily coincide with an immediate change in the executive. For instance, U.S. elections are always held on Tuesday following the first Monday of November, whereas the presidential term starts on the 20^{th} of January the following year. This study investigates the relationship between politics and stock markets by focussing both on the entire term of office and on the particular day voters cast their ballots.

It is conceivable that in the face of political changes investors adjust their required risk premium on assets. If they attribute greater uncertainty to the left of the political scene, the stock market will be expected to offer higher returns under left-wing incumbencies. The higher returns would be a form of compensation for the increased risk. In this scenario, however, the prices on Election Day are likely to plummet. This is an immediate consequence of the increased discount rate and the resultant lower present value of future cash flows of all firms. The story of changing risk premia is consistent with the previously discussed presidential puzzle (Santa-Clara and Valkanov (2003)) and Riley and Luksetich (1980) findings showing the existence of negative returns around Election Day for Democratic victories and positive returns for Republican wins.

[Insert Figure 2.1 here]

In its first step, this analysis examines international stock market patterns around Election Day using a simple event study. The abnormal returns are defined as difference between the returns on the respective MSCI Country Index and the MSCI World Index. Figure 2.1 depicts the cumulative abnormal returns separated by orientation of the election winner. The plots show no apparent market reaction around the day when the uncertainty about future political leadership is resolved. The cumulative abnormal returns for the right-wing and left-wing election winners oscillate within a narrow range and fail to reach statistical significance. Consequently, the conclusion that investors re-adjust their discount rates in response to election results is not supported in our data. It is also unlikely that highly profitable trading strategies based on the predictions of election outcomes can be designed.

2.2.4.2 Returns during the Term of Office

Having established that the announcement effect around elections is negligible, our focus turns to measuring stock market performance throughout different incumbencies. Table 2.6 presents the U.S. dollar denominated annualized returns corresponding to calendar years of tenure.[22] The second column shows mean returns under left-wing rules and is juxtaposed with the third column which reports similar statistics for the right-wing governments. A bootstrap test based on 1,000 replications is used to verify whether the difference between these two columns is equal to zero.

[Insert Table 2.6 here]

According to Table 2.6, the Democrat premium in the U.S. is around 7.7% per annum, which is in line with the findings of previous studies using value-weighted indices (see Huang (1985), Johnson, Chittenden, and Jensen (1999), and Santa-Clara and Valkanov (2003)). The U.S. experience does not, however, generalize in the global context. A closer inspection reveals that 14 out of the 24 considered stock markets actually offered a right-wing government premium (yet not statistically significant). Out of the five cases with bootstrap p-value below 10%, two favored right-wing governments and three favored the political left. Overall, the stock market returns were 34 basis points higher when the left-wing cabinets were in power, but this result is not statistically significant. In light of these findings, international investors should exercise a great deal of caution whenever speculating on the orientation of the executive.

[22] We present nominal stock market returns. Adjusting for inflation, however, does not alter our qualitative results and main conclusions.

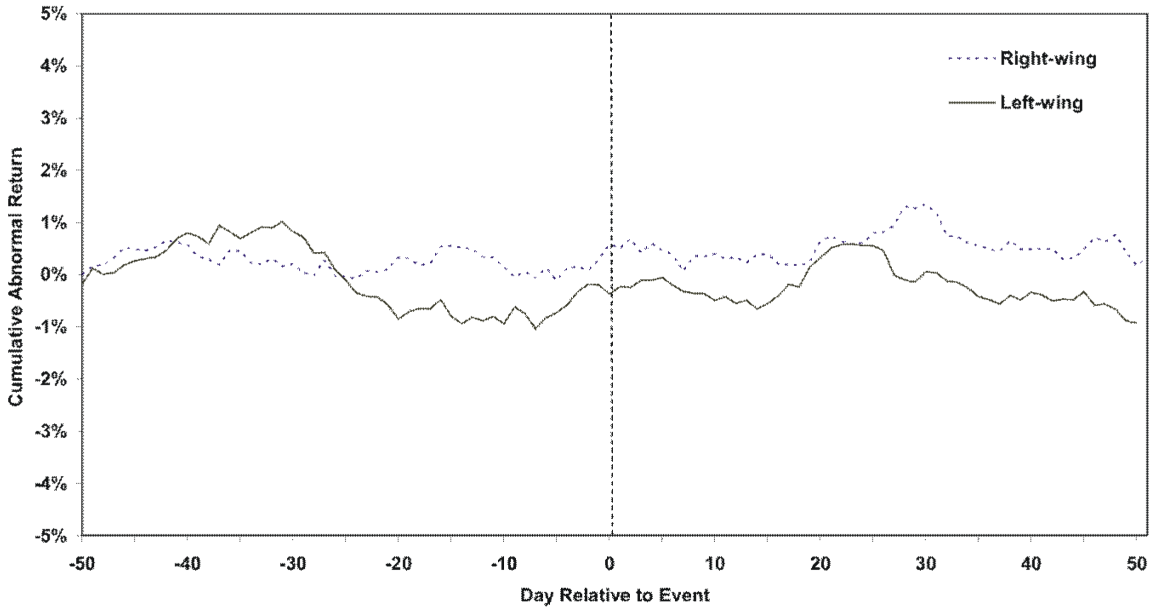
2.2.5 Summary and Conclusions

Several earlier papers noted that U.S. stock prices tend to grow faster when Democrats are in office (see, e.g., Huang (1985), Johnson, Chittenden, and Jensen (1999), Santa-Clara and Valkanov (2003)). This anomaly persisted for almost a century and opportunities to exploit it in security trading were present. Since political orientation of the incumbent president is common knowledge, this result may *prima facie* appear as a violation of the Efficient Market Hypothesis. Alternatively, it may be interpreted as an increased risk premium accruing to investors who decide to hold stocks throughout the tenure of left-wing administrations. If the latter explanation was correct, one would expect high returns during left-wing rules not only in the U.S. but also in other countries.

To verify the above-mentioned hypothesis, this study uses a comprehensive data set covering 24 OECD countries and 173 governments. The results based on the international sample indicate that there are no statistically significant differences in returns between left-wing and right-wing governments neither in the election period nor throughout the tenure. The anomaly observed in the U.S. appears to be country-specific and investors who diversify their portfolios internationally should be wary of allocating their money based solely on the political orientation of the countries' leadership. The evidence reported here lends support to the notion of efficient markets and randomness of stock prices (Fama (1970)).

2.2.6 Figures and Tables

Figure 2.1: Cumulative Abnormal Returns across Political Camps



Note: This figure depicts cumulative abnormal returns around Election Day (Day 0) for right-wing and left-wing government wins. In instances where elections took place during the weekend, Day 0 is defined as the first day of trading after the elections. Abnormal returns are calculated as the difference between the return on the respective MSCI Country Index and the MSCI World Index. They are subsequently averaged across all relevant events and cumulated over time to obtain the cumulative abnormal return.

Table 2.5: Sample Description

Country	MSCI Index Starting Date	Number of Left-Wing Govern-ments	Number of Right-Wing Govern-ments	Number of Days Left-Wing Government in Office	Number of Days Right-Wing Government in Office
Australia	01-Jan-80	5	6	4,749	4,382
Austria	01-Jan-80	6	2	7,339	1,792
Belgium	01-Jan-80	2	6	1,999	7,132
Canada	01-Jan-80	5	3	5,734	3,397
Czech Republic	30-Dec-94	2	2	2,359	1,295
Denmark	01-Jan-80	5	6	4,211	4,920
Finland	01-Jan-87	5	1	5,126	1,448
France	01-Jan-80	4	4	5,346	3,785
Germany	01-Jan-80	4	5	3,261	5,870
Greece	01-Jun-01	1	1	1,013	296
Hungary	02-Jan-95	2	1	2,230	1,421
Italy	01-Jan-80	6	3	7,487	1,644
Japan	02-Jan-80	1	9	885	8,245
Mexico	01-Jan-88	3	1	4,718	1,491
Netherlands	01-Jan-80	2	7	2,891	6,240
New Zealand	02-Jan-87	4	3	3,248	3,325
Norway	01-Jan-80	5	5	5,029	4,102
Poland	01-Jan-93	2	2	2,635	1,747
Portugal	04-Jan-88	2	3	2,350	3,856
Spain	01-Jan-80	5	3	5,161	3,970
Sweden	01-Jan-80	6	2	7,021	2,110
Turkey	04-Jan-88	2	4	1,407	4,799
United Kingdom	01-Jan-80	3	4	2,800	6,331
United States	01-Jan-80	3	5	3,307	5,824
Overall		85	88	92,306	89,422

Note: The first column lists all of the 24 OECD countries included in the sample. The dates from which daily stock prices for the respective MSCI Country Indices became available in Datastream are shown in the second column. For any given country, the number of left-wing and right-wing governments that were in office between the index start date and the end of 2005 are indicated, as well as the overall number of days corresponding to the tenures of either political camp.

Table 2.6: Political Orientation of Government and Stock Market Returns

Country	Returns (%)			
	Left-Wing	Right-Wing	Difference	Bootstrap p-Value
Australia	11.0897	2.0911	8.9986	0.1140
Austria	4.5204	19.4968	−14.9764	0.0490**
Belgium	2.3024	9.8324	−7.5300	0.2060
Canada	5.6661	7.7861	−2.1200	0.3680
Czech Republic	18.1543	−3.9685	22.1228	0.0730*
Denmark	−0.8029	13.3258	−14.1287	0.1090
Finland	9.9560	12.9370	−2.9810	0.4440
France	13.4530	1.5492	11.9038	0.0690*
Germany	−4.1297	14.1892	−18.3189	0.0160**
Greece	3.1633	31.0425	−27.8792	0.1480
Hungary	33.4150	−5.9310	39.3460	0.0190**
Italy	10.9697	2.9079	8.0618	0.2260
Japan	0.4352	7.9392	−7.5041	0.2690
Mexico	20.1139	13.8611	6.2528	0.3610
Netherlands	4.9962	11.1087	−6.1125	0.2330
New Zealand	−3.9651	3.0679	−7.0330	0.2460
Norway	3.3169	9.9913	−6.6744	0.2020
Poland	8.0489	28.1800	−20.1311	0.1690
Portugal	4.5779	0.3350	4.2429	0.3320
Spain	12.4139	3.0942	9.3197	0.1270
Sweden	15.0895	9.7092	5.3803	0.3030
Turkey	0.9501	8.2212	−7.2711	0.3670
United Kingdom	3.1467	10.6031	−7.4564	0.1490
United States	13.9556	6.2568	7.6988	0.1230
Overall	8.6992	8.3588	0.3404	0.5580

Note: The first column lists all of the 24 countries included in our sample. The next two columns report annualized US$-denominated average stock market returns during the tenure of left-wing and right-wing governments. Column 4 shows the difference between the two estimates. The last column lists the bootstrap p-values for the null hypotheses that the differences in column 4 equal zero. The bootstrap procedure was performed as follows: For a single bootstrap, sample returns were drawn at random with replacement to match the number of days in office for the left-wing and right-wing governments in our original sample. Subsequently, the annualized average returns for both camps were computed and the difference was recorded. This procedure was repeated 1,000 times to develop an empirical distribution for the difference under the null and the p-value was extracted from this distribution. ** and * denote statistical significance at the 5% and 10% level, respectively.

Chapter 3

Stock Market Volatility around National Elections[1]

3.1 Motivation

Country's politics can exert significant influence on its income distribution and prosperity. In democratic states, voters elect parties which best represent their personal beliefs and interests. According to partisan theory propounded by Hibbs (1977), leftist governments tend to prioritize the reduction of unemployment, whereas right-wing governments attribute higher social costs to inflation. Another influential theory presented by Nordhaus (1975) postulates that, irrespective of their political orientation, incumbents will pursue policies that maximize their chances of re-election. As a result, they will try to self-servingly attune the business cycle to the timing of elections. The economy will be stimulated by unsustainable expansionary policies before the elections, and harsh actions aimed at curbing the resultant inflation will have to follow at the beginning of the new term of office. It has to be noted, however, that any policy-induced cycles in real activity will be ephemeral if the economic agents and voters have rational expectations (Alesina (1987), Rogoff (1990)).

Several recent papers look at whether security returns are impacted by politics. Booth and Booth (2003) report that the U.S. stock market tends to perform better in the second half of the presidential term. This phenomenon could be a reflection of the political business cycle but can also be explained behaviorally. The authors argue that investors may be over-optimistic about the implications of the impending elections, but their optimism wears off quickly once the new administration fails to keep its

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election campaign promises. Santa-Clara and Valkanov (2003) show that the market excess return was higher under Democrat than Republican presidencies throughout the period from 1927 to 1998. This anomaly cannot be explained away by variation in business condition proxies. Additional evidence is provided by Nofsinger (2007), who contends that the stock market is a barometer of public sentiment and its movements can indicate whether incumbents will be re-elected.

Our inquiry adds to the discussion on the interplay between politics and stock prices in meaningful ways. Most of the previous empirical studies focus exclusively on U.S. data.[2] Since elections are essentially rare events, the single-country approach leads to a small sample and many statistical problems specific to it. To overcome this obstacle, the data set compiled for this study covers 27 industrialized nations. Furthermore, the basic conceptual framework proposed here departs slightly from the convention adopted in prior literature. Instead of examining the fortunes of the stock market throughout the tenure of different administrations, this analysis concentrates on the return variability around election dates. Evidence of extreme price movements in these periods will lend support to the conjecture that market participants tend to be surprised by the actual election results.

The investigation into return volatility is warranted on at least three grounds. First, the uncertainty about the election outcome has important implications for risk-averse investors. Prior research has shown that investors are undiversified internationally and exhibit a significant home bias (French and Poterba (1991), Baxter and Jermann (1997)). Since they hold predominantly domestic assets, the country-specific political risk will not diffuse in their portfolios. Consequently, the sole event of elections in their home country could have serious implications for the risk level of their portfolios. Second, any market-wide fluctuations in response to election shocks will augment the systematic volatility of all stocks listed. It is therefore conceivable that option prices could increase around the time when voters cast their ballots. Finally, the results reported here can be of interest to pollsters as they provide indirect evidence on whether the accuracy of pre-election forecasts suffices for practical applications. An observation of substantial volatility hikes around Election Day would indicate that the

[2] In addition to the aforementioned Booth and Booth (2003), Santa-Clara and Valkanov (2003), and Nofsinger (2007), several earlier papers deal with the issue of an election cycle in U.S. security returns. See Niederhoffer, Gibbs, and Bullock (1970), Allvine and O'Neill (1980), Riley and Luksetich (1980), Herbst and Slinkman (1984), Huang (1985), Stovall (1992), Gärtner and Wellershoff (1995), Hensel and Ziemba (1995), and Johnson, Chittenden, and Jensen (1999).

efforts to formulate precise predictions should be furthered and additional resources need to be directed towards this end.

The remainder of this chapter is organized as follows. Section 3.2 provides a systematic review of the techniques used in election forecasting and discusses the accuracy of these techniques. Section 3.3 outlines the methodological framework in which the null hypothesis of no election surprise is tested. The description of the data set and discussion of empirical results follow subsequently, in Sections 3.4 and 3.5. Sections 3.6 and 3.7 investigate the robustness of results and implications for investors. Section 3.8 concludes the chapter.

3.2 Predicting Election Outcomes

Public opinion surveying has become an integral part of today's political landscape. In the heat of election campaigns, the results of major surveys appear as cover-page stories, and politicians commission private polls, which provide them with strategic information. Pre-election surveying has a long and intriguing history, but it has to be noted that many of the early polls were plagued with serious methodological problems, which rendered their predictions unreliable (Squire (1988), Cahalan (1989)). It was not until the 1930s that scientific procedures such as quota sampling were introduced (Gallup and Robinson (1938)). Having realized the importance of appropriate sample selection, polltakers began improving their statistical apparatus, gradually moving towards probability sampling and other hybrid methods.

When conducting a survey, canvassers can interview subjects face-to-face, either by intercepting them on the street or by visiting sampled households. The unit costs of face-to-face interviewing can be quite high, especially if attempts to create a geographically representative sample are made. For this reason, the polling industry abandoned this method and embraced telephone-based surveys. The phone numbers of respondents could be drawn at random from a telephone directory. However, to avoid any sample biases arising from the systematic exclusion of households with unlisted phone numbers, pollsters tend to use random digit dialing systems. Random digit dialing is employed by major American polling organizations in their presidential election polls (Voss, Gelman, and King (1995)). The results of recent research indicate that this technique may be soon superseded by the more cost-effective and reliable method of sampling from the voter registration lists (Green and Gerber (2006)).

The accuracy of survey-based projections may depend on multiple factors, such as sampling procedure, number of respondents, or correct identification of likely non-voters. With their reputation at stake, pollsters are motivated to reduce the margin of error by applying the best techniques at their disposal, especially in the case of widely followed national elections. For this reason, the major pre-election surveys have enjoyed a reasonably good track record ever since scientific polling was adopted. It can be calculated from the data released by the National Council on Public Polls (NCPP) that the average absolute candidate error for all major U.S. presidential polls between 1936 and 2000 was 2.32%.[3]

Election forecasting also embraces techniques other than polling. For instance, one could make use of the fact that election outcomes tend to correlate with macroeconomic variables (Kramer (1971), Grier and McGarrity (1998)). This correlation is observed because many voters assess economic conditions retrospectively and hold incumbents accountable for the efficacy of their policies. Fair (1978) formalized this intuition by deriving a model which links the share of two-party vote to such factors as GDP growth and inflation. He made subsequent updates of his vote equation and provided forecasts for presidential elections (Fair (1982), Fair (1988), Fair (1996), Fair (2002)).[4] The ex-post within-sample prediction of Fair's model has been correct with respect to the election winner in all but three presidential races held since 1916. The average absolute error of the out-of-sample forecasts in the ten elections starting from 1964 equaled 2.58% (Fair (2004)).

In general, rational investors will strive to assess voter sentiment using all available sources of information, such as polls, macroeconomic data, electoral debates, or media reports. In an efficient market, their expectations will be aggregated into a consensus forecast, and stock prices will move to reflect it. A wealth of empirical evidence on how markets aggregate expectations of individual traders comes from prediction markets[5] like the Iowa Electronic Markets (IEM).[6] These markets are operated by the faculty of Tippie College of Business at the University of Iowa and allow individuals to stake their money on future election results.

[3] See the report of O'Neill, Mitofsky, and Taylor (2001).

[4] Ray C. Fair makes available all updates on his Yale web site at `http://fairmodel.econ.yale.edu/`.

[5] For an introduction to types, functioning, and applications of prediction markets the interested reader is referred to Wolfers and Zitzewitz (2004).

[6] For an illuminating overview of historical presidential betting markets in the U.S. during the 1868–1940 era see Rhode and Strumpf (2004).

The IEM is essentially a futures market where trading can be conducted over the Internet on a 24-hours-per-day basis. Different types of contracts are listed. In the presidential vote-share market, the contracts' liquidation payoff is a dollar multiple of the popular vote percentage received by a given candidate. In the winner-takes-all market, contracts are defined as digital options with a payoff of $1 conditional on a particular candidate winning the election. The design of the instruments traded on the IEM allows the expected election outcome to be easily extracted from the prevailing market prices.[7]

Prior research has documented that, although individual traders in the IEM show an inclination to overestimate the chances of their preferred candidate and often conduct suboptimal transactions, the market in aggregate is an exceptionally accurate predictor of the election result (Forsythe, Rietz, and Ross (1999), Oliven and Rietz (2004)). The efficiency of market prices seems to be assured by marginal traders who arbitrage away any existing judgment biases and pricing errors. The prices of contracts are a much better guide to the future than polls. An analysis of 15 national elections in six different countries performed by Berg, Forsythe, Nelson, and Rietz (2005) reveals that the absolute error of polls in the week before the election was 1.93%, compared with a 1.58% average market error. Furthermore, the IEM outperformed over 70% of the long-horizon forecasts generated by polling organizations (Berg, Nelson, and Rietz (2003)). New opinion-poll results did not drive the market prices and were merely a confirmation of the traders' collective knowledge (Forsythe, Nelson, Neumann, and Wright (1992)).

The preceding discussion characterizes a broad spectrum of techniques and information that can be used to evaluate the mood of the electorate. The extant evidence indicates that reasonably accurate predictions of voters' behavior can be formed, but whether stock market participants are surprised by the ultimate election outcome remains an open empirical question.

3.3 Methodology

We gauge the impact of elections on the second moment of return distribution using a volatility event-study approach. The analysis starts with isolating the country-specific

[7] More information about the structure of the IEM can be found at `http://www.biz.uiowa.edu/iem/`.

component of variance within a GARCH(1,1) framework.[8] An international market model[9] is formalized as follows:

$$R_{i,t} = \alpha + \beta R_t^* + \varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim N(0, h_{i,t}), \tag{3.1}$$

$$h_{i,t} = \gamma_0 + \gamma_1 h_{i,t-1} + \gamma_2 \varepsilon_{i,t-1}^2, \tag{3.2}$$

where $R_{i,t}$ and R_t^* are the continuously compounded returns on the U.S. dollar denominated stock market index in country i and the global stock market index on day t, respectively. $\varepsilon_{i,t}$ denotes the country-specific part of index returns, and $h_{i,t}$ stands for its conditional volatility.[10,11]

Equations (3.1) and (3.2) are estimated jointly using the Maximum Likelihood (ML) method over a period immediately preceding the event window. The convention adopted in the literature for the type of event studies described by Brown and Warner (1985) is to use 250 daily returns to estimate the benchmark model. One year of daily observations, however, may be insufficient to accurately model GARCH processes, and a longer estimation window is called for. On the other hand, the use of an over-expansive window will substantially cut the number of elections that can be included in our sample. Guided by these practical considerations and the results of Hwang and Valls Pereira (2006), we have decided to choose an estimation period of 500 trading days.

To measure abnormal volatility, one has to consider the variation in $\varepsilon_{i,t}$ around the event date in relation to its regular non-event level. The GARCH model may serve as a benchmark, as it can provide an indication of what the volatility would have been, had the election not occurred. A word of caution, however, is required. As it stands, Equation (3.2) is a one-step-ahead forecast and will not generate an event-independent projection. The immediate impact of an election, as measured by $\varepsilon_{i,0}$, will have a

[8] The parsimonious GARCH(1,1) specification is in accord with previous volatility event studies (Hilliard and Savickas (2002)). Moreover, this parameterization has been found to exhibit the best fit and forecast accuracy (Akgiray (1989)).

[9] As a reference see Stehle (1977), for example.

[10] Given the assumption of normality for the GARCH(1,1) residuals, the distribution of the test statistic under the null hypothesis of zero cumulative abnormal volatility (Equation (3.7)) will be chi-square (Hilliard and Savickas (2002)). We agree with these authors that modelling GARCH(1,1) in which the conditional distribution of residuals is Student-t would be an interesting direction for further research and help accommodate the often empirically observed leptokurtosis of GARCH(1,1) residuals. However, this is beyond the scope of this paper.

[11] The incorporation of trading volume into the setting of this investigation would be a possible extension since price (return) and quantity (volume) are determined simultaneously and volume can also serve as an ex-post indicator of uncertainty (Karpoff (1986), Grundy and McNichols (1989), Kim and Verrecchia (1991), Harris and Raviv (1993)). However, volume data are unavailable in Datastream for the breadth and length of our sample.

bearing on the values of $h_{i,t}$ for any $t > 0$. This issue can be easily resolved by making the volatility forecast[12] conditional only on the information set available prior to the event. For this reason, the volatility benchmark for the k-th day of the event window is defined as a k-step-ahead forecast of the conditional variance based on the information set available on the last day of the estimation window t^*:

$$E\big[h_{i,t^*+k}|\Omega_{t^*}\big] = \hat{\gamma}_0 \sum_{j=0}^{k-1} (\hat{\gamma}_1 + \hat{\gamma}_2)^j + (\hat{\gamma}_1 + \hat{\gamma}_2)^{k-1} \hat{\gamma}_1 h_{i,t^*} + (\hat{\gamma}_1 + \hat{\gamma}_2)^{k-1} \hat{\gamma}_2 \hat{\varepsilon}^2_{i,t^*}. \tag{3.3}$$

The distribution of the residuals during the event window can be described as $\varepsilon_{i,t} \sim N\big(AR_t, M_t \cdot E\big[h_{i,t}|\Omega_{t^*}\big]\big)$, where M_t is the multiplicative effect of the event on volatility, AR_t is the event-induced abnormal return, and $t > t^*$. Under the null hypothesis that investors are not surprised by election outcomes, the value of parameter M_t should equal one. Note that, if the residuals were demeaned using the cross-section average, they would be normally distributed with zero mean. Their variance, under the assumption of residual orthogonality, would be

$$\begin{aligned} Var\Big[\varepsilon_{i,t} - \frac{1}{N}\sum_{i=1}^{N}\varepsilon_{i,t}\Big] &= M_t \Big[E\big[h_{i,t}|\Omega_{t^*}\big]\frac{N-2}{N} + \frac{1}{N^2}\sum_{j=1}^{N} E\big[h_{j,t}|\Omega_{t^*}\big]\Big] \\ &= M_t \cdot EIDRV_{i,t}, \end{aligned} \tag{3.4}$$

where $EIDRV_{i,t}$ stands for the event-independent demeaned residual variance and N is the number of events included in the sample.

Since the objective of the study is to quantify the effect of elections on stock market volatility, M_t is the parameter of primary interest. The method of estimating this event-induced volatility multiple rests on combining residual standardization with a cross-sectional approach in the spirit of Boehmer, Musumeci, and Poulsen (1991) and Hilliard and Savickas (2002). Note that the estimate $\hat{M}_t$ can be calculated as the cross-sectional variance of demeaned residuals, standardized by the event-independent demeaned residual standard deviation $[EIDRV_{i,t}]^{1/2}$:

$$\hat{M}_t = \frac{1}{N-1}\sum_{i=1}^{N} \frac{\big(N \cdot \hat{\varepsilon}_{i,t} - \sum_{j=1}^{N} \hat{\varepsilon}_{j,t}\big)^2}{N \cdot (N-2) \cdot E\big[h_{i,t}|\Omega_{t^*}\big] + \sum_{j=1}^{N} E\big[h_{i,t}|\Omega_{t^*}\big]}, \tag{3.5}$$

where $\hat{\varepsilon}_{i,t} = R_{i,t} - (\hat{\alpha} + \hat{\beta} R^*_t)$ and $t > t^*$.

Under the null hypothesis, the demeaned standardized residuals follow a standard normal distribution because M_t equals one. Consequently, the abnormal percentage

[12] For extensive reviews of the recent work on volatility forecasting see Poon and Granger (2003), Ederington and Guan (2005), or Andersen, Bollerslev, Christoffersen, and Diebold (2005).

change in volatility on any day t of the event window is $(\hat{M}_t - 1)$. For an event window (n_1, n_2), the cumulative abnormal volatility (CAV) can be calculated as

$$CAV(n_1, n_2) = \Big(\sum_{t=n_1}^{n_2} \hat{M}_t\Big) - (n_2 - n_1 + 1). \tag{3.6}$$

In the current setting, the null hypothesis of no impact can be expressed in the following way:

$$H_0 : CAV(n_1, n_2) = 0, \tag{3.7}$$

which is equivalent to

$$H_0 : \sum_{t=n_1}^{n_2} M_t(N-1) = (n_2 - n_1 + 1) \cdot (N - 1). \tag{3.8}$$

Since, under the null, M_t is a variance of N independent $N(0,1)$ random variables, $\hat{M}_t(N-1) \sim \chi^2_{N-1}$ and $\sum_{t=n_1}^{n_2} \hat{M}_t(N-1) \sim \chi^2_{(N-1)\cdot(n_2-n_1+1)}$. The test statistic for the hypothesis stated in Equation (3.7) is therefore

$$\phi(n_1, n_2) = \sum_{t=n_1}^{n_2} (N-1) \cdot \hat{M}_t \sim \chi^2_{(N-1)\cdot(n_2-n_1+1)}. \tag{3.9}$$

The inferences based on the theoretical test will not be robust if the assumptions of the underlying econometric model are violated. Potential complications may arise from non-normality, cross-sectional dependence, or autocorrelation of the regression residuals $\varepsilon_{i,t}$. To circumvent these problems and reinforce our results, the statistical significance of the election impact is additionally tested using the bootstrap methodology of Efron (1979). More specifically, the cumulative abnormal volatility during the election period is compared with the empirical distribution of $CAVs$ simulated under the null hypothesis. The iterative procedure for generating the empirical distribution can be described as follows:

1. From the entire set of available countries and dates, randomly draw with replacement N country/date combinations to match the number of elections in the original sample.

2. Compute the cumulative abnormal volatility using Equation (3.6) for the randomly generated sample over the respective event window.

3. Repeat steps 1 and 2 5,000 times and sort the collection of resulting $CAVs$ in an ascending order to obtain the empirical distribution. The p-value can be defined as the number of bootstrapped $CAVs$ that exceed the CAV calculated for the original election sample, divided by the number of replications (i.e. 5,000).

The changes in volatility are also linked to election and country characteristics by means of regression analysis. This inquiry closely follows the approach of Dubofsky (1991) and Clayton, Hartzell, and Rosenberg (2005) in that the dependent variable is defined as the natural logarithm of the pre-event and event window volatility ratio. The application of the log transformation to the variance quotient reduces the skewness of the underlying data and thereby leads to more reliable t-statistics. The test statistics and parameter standard errors are estimated using the heteroskedasticity-consistent method of White (1980). A description of the independent variables used in the regressions follows in Subsection 3.4.

3.4 Data

In an attempt to create a broad international sample, the author compiled information on 27 industrialized nations. This includes all OECD countries, with the exception of Iceland, Luxembourg, and Slovakia.[13] As of the time of writing this chapter, Morgan Stanley Capital International Inc. (MSCI) did not provide data on stock market indices for these three capital markets. The returns for the remaining countries were computed using the U.S. dollar denominated MSCI Country Indices. These are value-weighted and adjusted for dividend payments. We have further chosen the MSCI World Index, which measures the performance of all developed equity markets, as a proxy for our global portfolio. The stock market data are sourced from Thomson Financial Datastream.

[Insert Table 3.1 here]

Table 3.1 summarizes some important facts about the 27 countries and 134 elections[14] included in our sample. As can be seen from the table, we distinguish between countries where parliamentary elections are assumed to be the relevant events and countries where presidential elections are investigated instead. This distinction is crucial since we combine a panel of countries with heterogeneous political systems and diverse constitutional features. In states with a presidential system of government, a

[13] This results in 21 developed markets (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, UK, U.S.) and 6 emerging markets (Czech Republic, Hungary, Korea, Mexico, Poland, Turkey). Or, put differently, 20 countries are located in the European region, 4 in the Asia-Pacific region, and 3 in the Americas.

[14] Concerning their distribution, 96 elections are clustered in Europe, 24 in the Asia-Pacific region, and 14 on the American continent.

President holds the positions of both head of state and head of government. Countries with presidential systems include the United States, Mexico, and South Korea. Most of the countries in our sample, however, operate under parliamentary systems with a Premier or Prime Minister as the head of government, and a President or Monarch as the, sometimes merely symbolic, head of state. Since our intention is to investigate the volatility around those elections that determine the formation of national governments, we have to focus on presidential elections in presidential systems and parliamentary elections in parliamentary systems.

Column 3 of Table 3.1 indicates the date from which daily observations on the respective MSCI Country Indices can be downloaded from Datastream. For several countries, monthly observations became available prior to the dates reported in Table 3.1. It has to be noted, however, that monthly sampling frequency is too low for the purposes of our inquiry. While the indices for most of the developed markets start around January 1980, other countries do not have these data available until the end of the 1980s or even the beginning of the 1990s. In some cases, this can quite heavily cut the number of elections that qualify for inclusion in our sample. The relative paucity of data in the time-series dimension vividly highlights the merits of a large cross-section.

Election dates were mostly obtained from Lane, McKay, and Newton (1997), Caramani (2000), and Banks, Muller, and Overstreet (2004). To double-check the integrity of these data, we conducted extensive newspaper and internet searches. For any given country, the date of the first election included is solely determined by the MSCI index starting date. Elections that took place in the first 500 trading days after the index starting date, however, had to be excluded from the sample. This restriction enables us to estimate the volatility benchmark model given in Equations (3.1) and (3.2) for all of the events considered. The date of the last election included (column 5) corresponds to the last election that took place before the end of 2004.

Column 6 reports the total number of elections for each of the countries. The maximum of nine elections for Australia can be explained by the early availability of index data for this country, combined with a relatively short election cycle of only three years and a considerable number of early elections. The minimum of only one observation is linked to Greece, which has the shortest MSCI index series. For four countries, only two elections can be included. Among these are the Eastern European emerging markets of Czech Republic, Hungary, and Poland, where stock exchanges were only re-established after the fall of communism at the beginning of the 1990s, and

Mexico, where the first election that met international standards of democracy and transparency was not held until 1994.

To pinpoint the determinants of election-induced volatility, we have constructed a comprehensive data set of explanatory variables. These variables are meant to provide further insights into the political, institutional, and socio-economic factors which could influence the magnitude of election shocks (see, for example, Alesina, Roubini, and Cohen (1997), Pantzalis, Stangeland, and Turtle (2000), and Beck, Clarke, Groff, Keefer, and Walsh (2001)). More specifically, the following explanatory variables are considered:

1. *Parliamentary* (dummy variable) captures the difference between parliamentary and presidential systems.

2. *Minority_Government* (dummy variable) indicates elections in which a minority government—i.e., a cabinet in a parliamentary system that does not represent a majority of seats in parliament—is brought to office.

3. *Margin_of_Victory* is defined as the difference between the percentage of popular votes obtained by government coalition and opposition for parliamentary elections, and the corresponding difference between winner and runner-up for presidential races.

4. *Number_of_Parties* indicates the number of independent political parties involved in the government coalition for parliamentary systems. It takes a value of 1 for presidential systems.

5. Δ*Orientation* (dummy variable) indicates a change in the political orientation of the government, i.e., a shift from a left-wing to a right-wing government or vice versa.[15]

6. *Early_Election* (dummy variable) marks early elections, i.e., elections that were called more than three months[16] before the official end of the term of the incumbent administration, as set at the beginning of the government's tenure.[17]

[15] The classification of governments into a left-wing/right-wing scheme is, of course, far from being uncontroversial and may be deemed subjective. Therefore, we stick closely to the conventions adopted in Alt (1985), Alesina and Roubini (1992), and Banks, Muller, and Overstreet (2004).

[16] This is in line with Pantzalis, Stangeland, and Turtle (2000). Alternative specifications classified elections as "early" whenever they took place more than six or twelve months before the official end of the term. Changes in the definition of this variable, however, did not substantially alter our empirical findings.

[17] A change in the timing of an election gives the market less time to analyze new information related to the election, thus forcing market participants to revise and re-evaluate their expectations in a shorter

7. *Compulsory_Voting* (dummy variable) indicates countries with mandatory voting laws.

8. *Ln_Population* is the natural logarithm of total population in a given country-year.

9. *Ln_GDP_per_Capita* is the natural logarithm of GDP per capita in a given country-year, measured in constant 2000 US$.[18]

The last two variables were obtained from the World Development Indicators[19] database compiled by the World Bank. The main sources considered and consolidated for the construction of the political variables are Alesina and Roubini (1992), Laver and Schofield (1998), Caramani (2000), Beck, Clarke, Groff, Keefer, and Walsh (2001), Naka (2002), Müller and Strøm (2003), and Banks, Muller, and Overstreet (2004). The information on compulsory voting comes from a comprehensive archive of the International Institute for Democracy and Electoral Assistance[20] (IDEA (2005)).

[Insert Table 3.2 here]

Table 3.2 reports descriptive statistics for the explanatory variables introduced above. Parliamentary elections account for 91.8% of our sample, and in almost one-fourth of the cases, the winning government coalition does not have a majority of seats in the parliament. In some countries (especially Denmark, Norway, and Sweden), minority governments are the rule rather than exception (Müller and Strøm (2003)). This observation may partially explain the negative average victory margin of −2.81%. Another explanation that can be offered for this negative mean is that most countries in our sample have incorporated majoritarian elements in their electoral systems, thereby favoring parties with higher vote shares. This implies that a popular vote share of less than 50% (obtained by either a single party or a multi-party coalition) is often sufficient for a majority of seats in parliament. The data reported in Table 3.2 also reveal that a median government coalition comprised two independent parties.

period of time (Pantzalis, Stangeland, and Turtle (2000)). This is consistent with manipulation by the incumbent during policy-sensitive elections as noted by Harrington (1993).

[18] For the last two variables, the log transformation is applied to reduce the skewness in the underlying data.

[19] The data can be found at `http://devdata.worldbank.org/wdi2006/`.

[20] The International IDEA Voter Turnout Website, accessible at `http://www.idea.int/vt/`, contains a global collection of political participation statistics.

In almost one-third of the cases, a change in the orientation of the government takes place, and 41.8% of the elections are called early. In some countries with endogenous election timing, governments may regularly be tempted to call early elections in order to exploit economic conditions which they judge more promising for their re-election (Cargill and Hutchison (1991)). Six of the countries in our sample (Australia, Belgium, Greece, Italy, Mexico, and Turkey) have mandatory voting laws, but the stringency and enforcement of these laws appears to be country-specific. A non-voter could, for instance, face a fine, restrictions on employment in the public sector (Belgium), or difficulties in obtaining new identification documents (Greece). Finally, the population of the countries included in our sample ranges from 3.4 million (New Zealand 1990) to 294 million (United States 2004), whereas GDP per capita (measured in constant 2000 US$) varies between US$ 2,471 (Turkey 1991) and US$ 38,222 (Japan 2003).

3.5 Results

3.5.1 Return Volatility around the Election Date

Our empirical investigation starts with the volatility event study described in the methodology subsection. For the purpose of our inquiry, we define the event day as the Election Day, except for instances when elections took place during the weekend or on a bank holiday. In these cases, day zero is defined as the first trading day after the election. The first panel of Figure 3.1 depicts the behavior of cumulative abnormal volatility around the vote-casting periods. The theoretical and bootstrap p-values for the null hypothesis of no increase in country-specific variance are plotted in the second and third panel. Both probabilities are truncated at 20%.

[Insert Figure 3.1 here]

The plot depicted in Figure 3.1 clearly demonstrates that elections are accompanied by elevated volatility. A strong abnormal rise starts on Election Day and continues for a number of days thereafter. This prolonged reaction is most probably due to the fact that the official results may not be released until several days after the elections. The process of counting special votes[21] and possible recounts can substantially add to

[21] The term "special votes" is used here in relation to votes cast by individuals who, due to certain circumstances, are unable to get to the required polling place on Election Day. This could, for instance, be the case when the registered voter is outside her electorate, is seriously ill or hospitalized, or her name was mistakenly omitted from the electoral roll.

this delay. Furthermore, some of the abnormal volatility observed in the later days of the event window may also be attributed to ongoing coalition talks or statements issued by the newly elected authorities.

[Insert Table 3.3 here]

It can be seen from Table 3.3 that $CAV(-25, 25)$ reaches a value of 11.94. At first glance, this value may have little intuitive content. An astute reader, however, will realize that the ratio of CAV to the total number of days included in the event window is, by construction, equal to the percentage increase of the volatility relative to its benchmark. This means that, in the 51 days surrounding the elections, the country-specific component of variance was 23.42% higher than it would have been, had the elections not occurred. Narrowing the event window leads to larger implied percentage changes, confirming that most of the large stock market moves are concentrated around Election Day. The punch line of Table 3.3 is that the country-specific return volatility can easily double in the week around elections.

Figure 3.1 shows the probabilities for the null of no abnormal reaction in volatility. The probabilities drop to nearly zero immediately after the event date. This result is corroborated in Table 3.3 where, at the precision of four decimal places, most of the p-values are indistinguishable from zero. Regardless of the testing methodology, the null is rejected for all of the considered event windows at the 1% significance level or better. There are slight differences between the p-values produced by the theoretical and bootstrap approaches. The latter can be deemed more reliable, as it does not assume normality and independence of returns. Overall, very compelling evidence is found that the country-specific component of variance increases dramatically around the event date.

3.5.2 Determinants of Election Surprise

We proceed further by attempting to link the magnitude of election shocks to several explanatory variables by means of regression analysis. Following the approach adopted in prior literature (Dubofsky (1991), Clayton, Hartzell, and Rosenberg (2005)), we define the dependent variable as a natural logarithm of the volatility ratio. This ratio is constructed by dividing the return variance computed over the $(-25, 25)$ event window by the variance of returns in a pre-event window of equal length, i.e. $(-76, -26)$. To check the sensitivity of the regression estimates to the addition of new independent variables, several specifications were tried, and the results are reported in Table 3.4. As can be seen from the table, the *Margin_of_Victory* and *Minority_Government* variables are not bundled together into one equation in order to avoid potential multicollinearity problems. There is a strong negative correlation between these variables of almost -0.5, which is induced by the fact that minority governments typically have a negative margin of victory.

[Insert Table 3.4 here]

Table 3.4 reveals that the increase in variance is more pronounced for closely contested races. Whenever picking the probable winner is difficult, uncertainty will not resolve fully until the official release of election results. Investors also tend to react in a more volatile manner when the new government coalition does not hold a majority of seats in parliament. This could be, for instance, because the implementation of new policies by minority governments is usually a very arduous task. A change in the political orientation of the executive also adds to the volatility of stock prices, as investors anticipate new directions in economic and redistribution policies.

We find evidence that mandatory voting reduces the election surprise. At least two explanations can be propounded to explain this phenomenon. In the absence of compulsory voting laws, individuals holding extreme political views will show an above-average proclivity to vote and will be able to distort election outcomes. Furthermore, the precision of pre-election polls will depend on whether the interviewers have correctly determined which of the respondents are likely not to vote. Political preferences of voters and non-voters may be quite different, which will bias the survey predictions (Green and Gerber (2006)). With compulsory voting laws in place, both of the above-mentioned problems are mitigated.

Although the remaining regressors lack significant explanatory power, the signs of their coefficient estimates appear to be uncontroversial. The jump in volatility is, *ceteris paribus*, greater for presidential races and in cases when the elections are called early. Formation of wide government coalitions comprising a large number of independent parties can further aggravate the stock market fluctuations. Finally, there seems to be less uncertainty about election outcomes in countries with large population and high GDP per capita, as numerous and affluent nations can allocate more resources to pre-election polling.

3.6 Robustness Checks

The event study presented in the previous subsection focusses on the country-specific component of volatility. An obvious extension of this analysis would be to investigate the behavior of total variance, which is influenced by both domestic and international developments. Table 3.5 reports the average unconditional variances computed for different time intervals around the elections. These figures are subsequently compared with the estimates of average variances from the pre-event windows of equal length. The evidence indicates that a marked increase in unconditional volatility takes place around the election date. Wilcoxon signed-rank (Wilcoxon (1945)) and Fisher (Fisher (1932)) tests are employed to affirm the statistical significance of this increase. Whereas the former has frequently been applied in the literature, to the best knowledge of the author there has not been a single application of the Fisher test in the event-study context as of yet. Consequently, some words of clarification are in order.

The design of the Fisher test has been inspired by the work of Fisher (1932) and Maddala and Wu (1999). The null hypothesis for this test can be written as

$$H_0 : \textit{Event Variance}_i = \textit{Pre-Event Variance}_i \textit{ for all } i, \tag{3.10}$$

against the alternative

$$\begin{aligned} H_1 : \textit{Event Variance}_i &> \textit{Pre-Event Variance}_i \\ &\textit{for a significant fraction of } i, \end{aligned} \tag{3.11}$$

where $i = 1, \ldots, N$ denotes the event subscript. Essentially, the null is a composite hypothesis because it imparts N sub-hypotheses. One could test the variance constancy for each i using a simple F-test, and the significance level p_i could be obtained. It follows that, under the null, $-2\ln(p_i)$ is χ^2 distributed with two degrees of freedom and the ultimate test statistic $\textit{Fisher Test} = -2\sum_{i=1}^{N}\ln(p_i)$ has a χ^2 distribution with $2N$ degrees of freedom.

[Insert Table 3.5 here]

Table 3.5 shows that, irrespective of the choice of the event window, both the Wilcoxon signed-rank and Fisher tests strongly reject the hypothesis of variance constancy. To illustrate the inflation in unconditional variance even further, we adopt a simple rolling regression approach which can be described as follows. Given any fixed day in the event window, we compute logged unconditional variances over the last 25 trading days for every election included in our sample. These logged variances are subsequently regressed against a constant term. This calculation is repeated for every day in the event window and the regression constants are plotted in Figure 3.2. The pattern that emerges strongly attests to the existence of election surprise.

[Insert Figure 3.2 here]

3.7 Implications for Investors

3.7.1 Compensation for Risk

It is commonsensical to expect increased return variability during periods of political change. It is, however, less obvious whether investors are adequately compensated for taking this political risk. To address this question, we conduct a simple event-study analysis (see, e.g., Campbell, Lo, and MacKinlay (1997)). We define abnormal returns (AR) as the difference between returns on the election country stock market index and the global index. The abnormal returns are subsequently averaged across all events and cumulated over the relevant event window (n_1, n_2) to obtain an estimate of cumulative abnormal return $\big(CAR(n_1, n_2)\big)$. The statistical significance of $CAR(n_1, n_2)$ is evaluated using the following t-statistic:

$$t\big(CAR(n_1, n_2)\big) = \frac{CAR(n_1, n_2)}{\sqrt{(n_2 - n_1 + 1) \cdot \hat{Var}(AR_t)}}, \tag{3.12}$$

where $\hat{Var}(AR_t)$ is the estimate of variance of the average abnormal returns computed in the time-series dimension. Under the null hypothesis, the test statistic in Equation (3.12) follows a t-distribution with 499 degrees of freedom (see Brown and Warner (1985)), which can be approximated sufficiently accurately by a standard normal distribution.

The magnitude of $CARs$ reported in Table 3.6 and plotted in Figure 3.3 does not seem excessive. The additional compensation to an investor who is prepared to abandon a strategy of international diversification and invest all of her money in countries facing elections is about 33 basis points in the $(-25, 25)$ event window.[22] None of the reported $CARs$ in Table 3.6 is statistically significant, and several estimates for shorter subperiods are negatively signed. Although the reported risk premiums appear quite

[22] The positively signed estimate is consistent with the uncertain information hypothesis (UIH) of Brown, Harlow, and Tinic (1988) who note that as uncertainty is reduced, price changes tend to be positive on average.

modest, they would provide an adequate compensation if the average level of investors' risk aversion was sufficiently low.

Given certain assumptions, it can be shown[23] that a representative investor with constant relative risk aversion will be content with the risk compensation offered by the market if her relative risk-aversion (RRA) coefficient $\gamma(n_1, n_2)$ is below a certain break-point level $\gamma^B(n_1, n_2)$. If, on the other hand, $\gamma(n_1, n_2) > \gamma^B(n_1, n_2)$, the optimal decision for the investor will be to cease investing all of her money in countries awaiting elections and pursue a strategy of international portfolio diversification. The parameter $\gamma^B(n_1, n_2)$ can be estimated from the underlying data as follows:

$$\hat{\gamma}^B(n_1, n_2) = 1 + 2\frac{CAR(n_1, n_2)}{\hat{Var}\big[\tilde{R}_i(n_1, n_2)\big] - \hat{Var}\big[\tilde{R}^*(n_1, n_2)\big]}, \tag{3.13}$$

where $\tilde{R}_i(n_1, n_2)$ and $\tilde{R}^*(n_1, n_2)$ are the cumulative log returns on the election country index and the global index, respectively. $\hat{Var}\big[\tilde{R}_i(n_1, n_2)\big]$ and $\hat{Var}\big[\tilde{R}^*(n_1, n_2)\big]$ denote the estimates of cross-sectional variances thereof.

[Insert Figure 3.3 here]

[Insert Table 3.6 here]

The task of drawing any generalized conclusions, at this stage, should be approached with great caution, especially given the fact that the literature does not provide any consensus estimate of the average investors' risk aversion. An analysis of households' asset composition by Friend and Blume (1975) reveals that the RRA coefficient is slightly above two. Gertner (1993) examines risky decisions of contestants on the television game show "Card Sharks" and reports a lower bound for the risk-aversion estimate of 4.8. A similar study of the Dutch word game "Lingo" by Beetsma and Schotman (2001) concludes that the parameter is close to seven. Last but not least, the risk-aversion coefficient that is needed to explain the magnitude of the historical equity premium in the United States is around 19 (Mehra and Prescott (1985), Campbell, Lo, and MacKinlay (1997)).

The academic discussion on the risk attitudes of a representative agent is unlikely to be settled in the near future. Our pragmatic recommendation for anyone who considers investment in a country facing an election, however, would be to measure their own RRA coefficient. This individual estimate should be subsequently compared with the figures reported in the last column of Table 3.6 in order to determine the

[23] For a rigorous derivation and proof see the Appendix in Subsection 3.9.

optimal choice of strategy. It can be seen that an investment over the longest event window requires a risk-aversion coefficient of less than 1.57. Furthermore, one would have to exhibit risk-loving behavior to benefit from investments made on Election Day and liquidated within the next two weeks. A robust conclusion that can be reached is that everyone with an RRA coefficient greater than 4.21 should definitely avoid investing all of their money in a country with upcoming elections. The compensation for risk will, in this case, be incommensurate and the strategy of international portfolio diversification will yield higher expected utility.

3.7.2 Option Pricing and Possible Trading Strategies

Savvy investors are likely to realize that the stock market tends to be mercurial in nature during election periods. If they incorporate this information into their decision-making, prices of financial options will move to reflect it. This nexus between option market and political risk has not gone completely unnoticed in the literature. Gemmill (1992) reports that, in the last two weeks of the British 1987 election campaign, implied volatility of the FTSE 100[24] options almost doubled. Sharp increases were also observed for blue-chip companies that were likely to be re-nationalized if Labour won the election. These results illustrate the strong interdependence between the spot and option markets.

We check whether the findings of Gemmill (1992) can be reconfirmed in an international sample. The implied volatility indices are, however, unavailable for many of the countries considered, and most of them have not been constructed until the turn of this decade. The obtainable data permit an analysis of option market behavior around 15 elections[25] in 11 countries.[26] The time series are sourced from Thomson Financial Datastream and an exact description of the sample composition can be found in Table 3.7. Given the data at hand, an average implied volatility is computed across all elections and plotted in Figure 3.4.

[Insert Table 3.7 here]

[Insert Figure 3.4 here]

[24] FTSE is a British provider of stock market indices and was originally conceived as a joint venture between the Financial Times (F-T) and London Stock Exchange (S-E).

[25] Concerning their distribution, 10 elections are clustered in Europe, 2 in the Asia-Pacific region, and 3 on the American continent.

[26] This results in 8 developed markets (Austria, France, Germany, Japan, Netherlands, Switzerland, UK, U.S.) and 3 emerging markets (Czech Republic, Mexico, Poland).

Figure 3.4 offers compelling evidence that options tend to be more expensive in periods when voters cast their ballots. The average implied volatility jumps from 31.2% five days before the election to 55.5% five days thereafter. Interestingly, not much of the upward move is observed prior to the event. This may suggest that investors did not anticipate the extent of their surprise on Election Day. As a consequence, strategies of buying straddles and strangles prior to the elections could have proven quite lucrative (see, e.g., Hull (2005)). Although a more extensive study would be needed to affirm the profitability, our preliminary results indicate that these volatility-based option trading strategies may have had some success in the past.

3.8 Summary and Conclusions

This study investigates the interplay between politics and finance by focussing on stock market volatility around national elections. The value added of this chapter is twofold. First, it provides a detailed examination of the second moment of index return distribution around election dates. Since much of the uncertainty regarding future government policies is resolved during balloting periods, the stock prices can adjust dramatically and stock market volatility is likely to increase. To the best of the author's knowledge, it is the first study that rigorously quantifies the magnitude of this increase. Second, we stretch the limits of earlier research by overcoming the commonly used single-country approach and by introducing a new, extensive set of explanatory variables.

The impact of elections on country-specific stock market volatility is assessed in an event-study framework. Our empirical findings indicate that, despite many efforts to accurately predict election outcomes, investors are still surprised by the ultimate distribution of votes. Stock prices react strongly in response to this surprise, and temporarily elevated levels of volatility are observed. These empirical conclusions hold irrespective of the choice of event window. Narrowing the event window, however, magnifies the implied percentage change in variance, suggesting that most of this hike is due to large market moves on Election Day. We find that the country-specific component of volatility can easily double during the week surrounding elections.

To track down the main determinants of election-induced volatility, we have compiled an encompassing data set of political, institutional, and socio-economic variables. Four of the variables proved to influence the magnitude of election surprise in a significant way. Stock market participants tend to react in a more volatile manner during closely contested races, when the outcome of the election brings about a change in the political orientation of the government, and when governments do not secure parliamentary majorities. In all of these cases, investors perceive increased uncertainty. On the other hand, compulsory voting laws reduce the election shock. Enactment of such laws leads to higher voter turnout, which improves the accuracy of pre-election surveys and reduces the chances that the election outcome will be influenced by political fringe groups.

Our empirical findings are robust to alternative ways of measuring excess volatility around Election Day. When examining the total variance rather than its country-specific component, we still observe an evident jump. The statistical significance of this increase is reconfirmed by both parametric and non-parametric tests. The link between the magnitude of the election shock and the explanatory variables mentioned above also seems to be uncontroversial since these variables retain their statistical significance in alternative specifications of the regression equation.

The implications for investors are tangible and important. Risk-averse agents require an adequate premium whenever they need to take on additional risks. Typical investors are not fully diversified internationally, and it may occasionally happen that they see all of their wealth invested in a country with upcoming elections. Therefore, the investigation into whether investors are appropriately compensated for bearing political risk associated with elections is crucial. It turns out that the premium offered for the election risk is rather modest and acceptable only for investors with a relatively low degree of risk aversion. All other investors will attain higher expected utility by diversifying their portfolio internationally. Furthermore, we show that national elections can be considered as important events by the participants of option markets. In the heat of political changes, options tend to trade at higher implied volatilities.

In the light of the presented results, it becomes clear that the efforts to provide more accurate pre-election forecasts should still be furthered. Improvements in forecasting precision will help to bridge the gap between actual investors' requirements and the current state of the art. With the emergence of accurate prediction markets, however, one could envision that advances in this field can be achieved in the future.

3.9 Appendix

A representative agent is assumed to invest all of her initial wealth W_{n_1} in risky assets. The investment decision is made right now (time n_1), and the portfolio composition will remain unaltered until some future date n_2 at which the investment will be liquidated. The agent chooses to maximize the expectation of her constant relative risk-aversion (CRRA) utility function

$$U(\tilde{W}_{n_2}) = \frac{\left[W_{n_1} e^{\tilde{R}(n_1,n_2)}\right]^{(1-\gamma(n_1,n_2))}}{1-\gamma(n_1,n_2)}, \tag{3.14}$$

where $\tilde{R}(n_1,n_2)$ is the cumulative, continuously compounded return on the portfolio over the entire investment period and $\gamma(n_1,n_2)$ is the agent's relative risk-aversion (RRA) coefficient $\big(\gamma(n_1,n_2) \neq 1\big)$. Note that, although the RRA coefficient is allowed to vary across different investment horizons, for any fixed horizon it does not change across different investment alternatives.

Given the normality of $\tilde{R}(n_1,n_2)$, the expression for the expected utility of terminal wealth can be derived using a formula for the expected value of log-normal distribution:

$$\begin{aligned} E\big[U(\tilde{W}_{n_2})\big] &= \frac{\left[W_{n_1}\right]^{(1-\gamma(n_1,n_2))} \left[e\right]^{(1-\gamma(n_1,n_2))E[\tilde{R}(n_1,n_2)]+\frac{1}{2}(1-\gamma(n_1,n_2))^2 Var[\tilde{R}(n_1,n_2)]}}{1-\gamma(n_1,n_2)} \\ &= \frac{\left[W_{n_1} e^{E[\tilde{R}(n_1,n_2)]+\frac{1}{2}(1-\gamma(n_1,n_2))Var[\tilde{R}(n_1,n_2)]}\right]^{(1-\gamma(n_1,n_2))}}{1-\gamma(n_1,n_2)}. \end{aligned} \tag{3.15}$$

Suppose further that elections are scheduled to take place in the agent's home country during her investment period (n_1, n_2). It is assumed for simplicity that the agent can pursue only two mutually exclusive strategies. She could either invest domestically or diversify her portfolio internationally. Her expected utility is influenced by this choice of strategy as follows:

$$E\big[U(\tilde{W}_{n_2})\big] = \begin{cases} \frac{\left[W_{n_1} e^{E[\tilde{R}_i(n_1,n_2)]+\frac{1}{2}(1-\gamma(n_1,n_2))Var[\tilde{R}_i(n_1,n_2)]}\right]^{(1-\gamma(n_1,n_2))}}{1-\gamma(n_1,n_2)}, \\ \textit{domestic strategy}; \\ \\ \frac{\left[W_{n_1} e^{E[\tilde{R}^*(n_1,n_2)]+\frac{1}{2}(1-\gamma(n_1,n_2))Var[\tilde{R}^*(n_1,n_2)]}\right]^{(1-\gamma(n_1,n_2))}}{1-\gamma(n_1,n_2)}, \\ \textit{international strategy}; \end{cases} \tag{3.16}$$

where $\tilde{R}_i(n_1,n_2)$ and $\tilde{R}^*(n_1,n_2)$ denote the cumulative log return on the stock market index in the election country and the cumulative log return on the global stock market index, respectively.

Whenever $E\big[\tilde{R}_i(n_1,n_2)\big] \neq E\big[\tilde{R}^*(n_1,n_2)\big]$ and $Var\big[\tilde{R}_i(n_1,n_2)\big] \neq Var\big[\tilde{R}^*(n_1,n_2)\big]$, the agent will be indifferent between the two investment alternatives if and only if her risk-aversion coefficient $\gamma(n_1,n_2)$ is equal to a break-point RRA coefficient $\gamma^B(n_1,n_2)$, such that

$$\begin{aligned} &E\big[\tilde{R}_i(n_1,n_2)\big] + \frac{1}{2}\big(1-\gamma^B(n_1,n_2)\big)Var\big[\tilde{R}_i(n_1,n_2)\big] \\ &= E\big[\tilde{R}^*(n_1,n_2)\big] + \frac{1}{2}\big(1-\gamma^B(n_1,n_2)\big)Var\big[\tilde{R}^*(n_1,n_2)\big]. \end{aligned} \tag{3.17}$$

Solving the above equation for $\gamma^B(n_1,n_2)$ yields

$$\gamma^B(n_1,n_2) = 1 + 2\frac{E\big[\tilde{R}_i(n_1,n_2)\big] - E\big[\tilde{R}^*(n_1,n_2)\big]}{Var\big[\tilde{R}_i(n_1,n_2)\big] - Var\big[\tilde{R}^*(n_1,n_2)\big]}. \tag{3.18}$$

It can be shown that the agent's optimal investment decision, in the presence of election-induced volatility (i.e. $\Big[Var\big[\tilde{R}_i(n_1,n_2)\big] - Var\big[\tilde{R}^*(n_1,n_2)\big]\Big] > 0$), can be described as

$$\textit{Optimal Strategy}\,\big(\gamma(n_1,n_2)\big) = \begin{cases} \textit{invest domestically} \\ \textit{if } \gamma(n_1,n_2) < \gamma^B(n_1,n_2), \\ \\ \textit{diversify internationally} \\ \textit{if } \gamma(n_1,n_2) > \gamma^B(n_1,n_2). \end{cases} \tag{3.19}$$

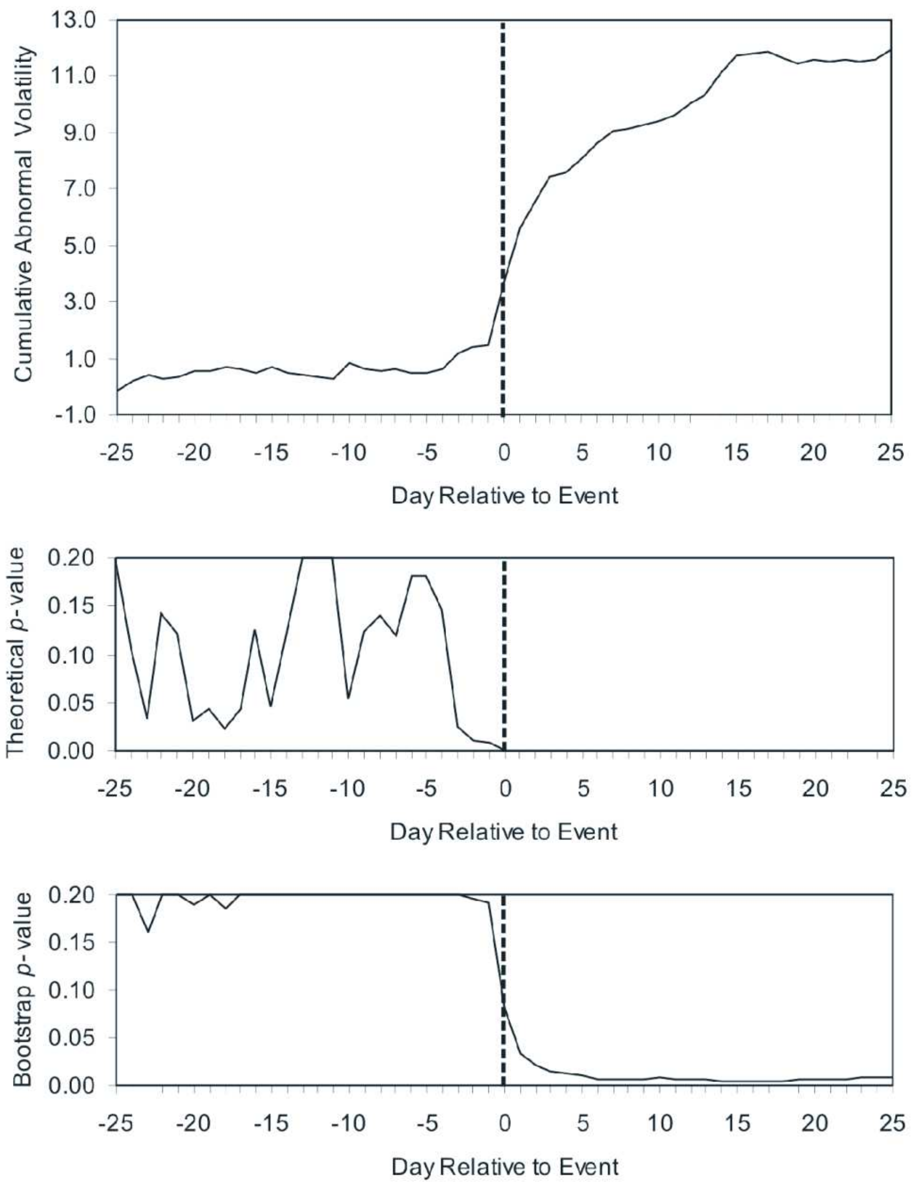
Equation (3.18) provides insights into the estimation of the break-point relative risk-aversion coefficient $\gamma^B(n_1,n_2)$ from the underlying data. Given that $CAR(n_1,n_2)$ is defined as cumulative excess return on the domestic market index over the international one, the estimator of $\gamma^B(n_1,n_2)$ can be written as

$$\hat{\gamma}^B(n_1,n_2) = 1 + 2\frac{CAR(n_1,n_2)}{\hat{Var}\big[\tilde{R}_i(n_1,n_2)\big] - \hat{Var}\big[\tilde{R}^*(n_1,n_2)\big]}, \tag{3.20}$$

where $\hat{Var}\big[\tilde{R}_i(n_1,n_2)\big]$ and $\hat{Var}\big[\tilde{R}^*(n_1,n_2)\big]$ denote the estimates of cross-sectional variances of cumulative log returns on the domestic and global stock market indices, respectively.

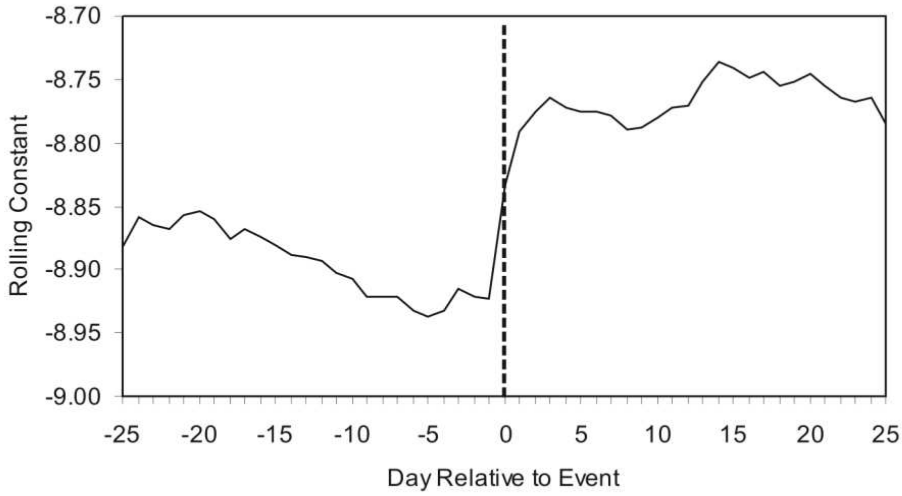
3.10 Figures and Tables

Figure 3.1: Cumulative Abnormal Volatility around Election Day



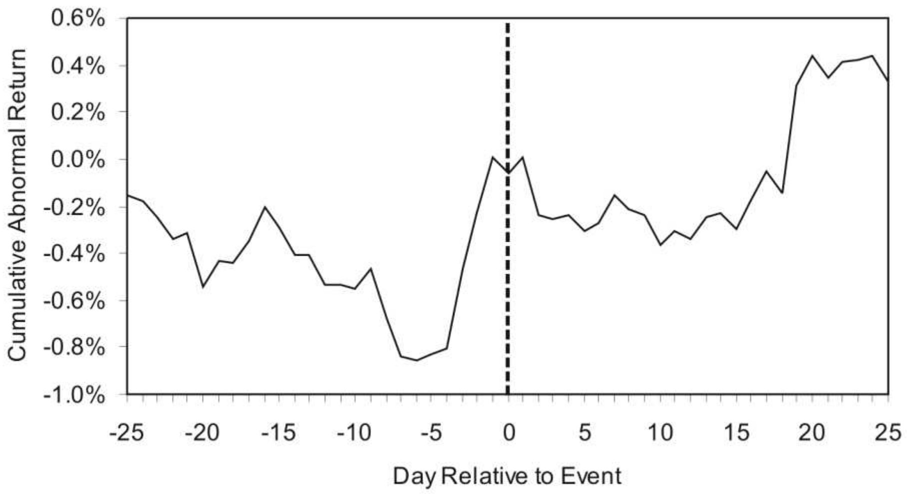
Note: The first panel plots the cumulative abnormal volatility around 134 national elections in 27 countries. The theoretical p-value shown in the second panel comes from a χ^2 test for the null hypothesis of no change in the country-specific component of volatility. The last panel depicts the p-value based on the empirical distribution of cumulative abnormal volatilities generated using 5,000 bootstrap samples. Both the theoretical and bootstrap p-values are truncated at the 0.2 level.

Figure 3.2: Rolling Regression Intercept



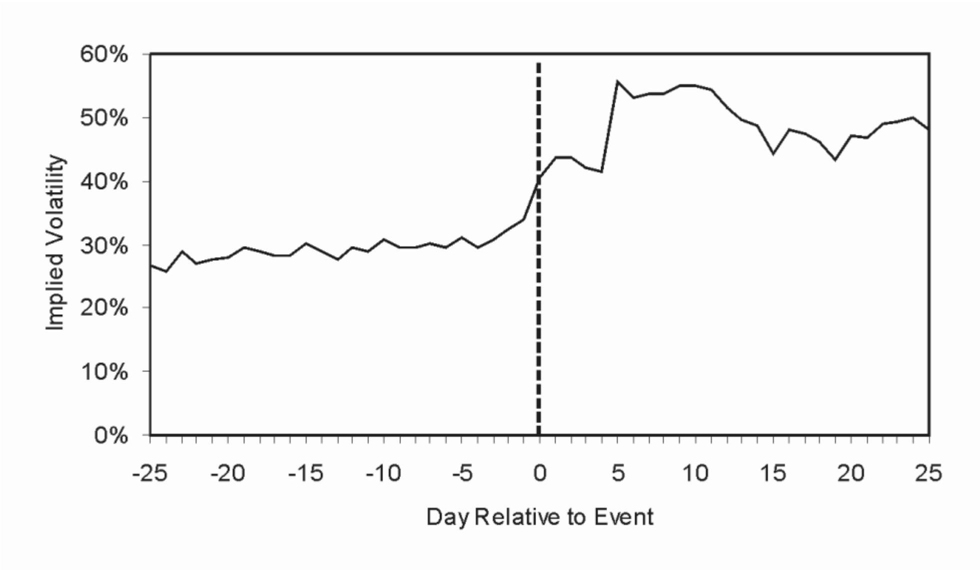
Note: Given any fixed day in the event window, logged unconditional variances over the last 25 trading days are computed for 134 elections included in our sample. The logged variances are subsequently regressed against a constant term. This calculation is repeated for every day in the event window, and the constant is plotted in the graph above.

Figure 3.3: Cumulative Abnormal Return around Election Day



Note: The abnormal returns are defined as the difference between returns on the election country stock market index and the global index. The abnormal returns are subsequently averaged across all 134 elections and cumulated over the relevant event window. The resulting estimate of cumulative abnormal return is plotted above.

Figure 3.4: Average Implied Volatility around Election Day



Note: This figure plots the average of implied volatility indices around 15 national elections held in 11 countries.

Table 3.1: Data Availability and Sample Composition

Country	Election Type	MSCI Index Start Date	First Election Included	Last Election Included	Number of Elections
Australia	Parliamentary	01-Jan-80	05-Mar-83	09-Oct-04	9
Austria	Parliamentary	01-Jan-80	24-Apr-83	24-Nov-02	7
Belgium	Parliamentary	01-Jan-80	13-Oct-85	18-May-03	6
Canada	Parliamentary	01-Jan-80	04-Sep-84	28-Jun-04	6
Czech Republic	Parliamentary	04-Jan-94	20-Jun-98	14-Jun-02	2
Denmark	Parliamentary	01-Jan-80	10-Jan-84	20-Nov-01	7
Finland	Parliamentary	01-Jan-87	17-Mar-91	16-Mar-03	4
France	Parliamentary	01-Jan-80	16-Mar-86	09-Jun-02	5
Germany	Parliamentary	01-Jan-80	03-Mar-83	22-Sep-02	6
Greece	Parliamentary	01-Jun-01	07-Mar-04	07-Mar-04	1
Hungary	Parliamentary	02-Jan-95	10-May-98	07-Apr-02	2
Ireland	Parliamentary	04-Jan-88	25-Nov-92	18-May-02	3
Italy	Parliamentary	01-Jan-80	26-Jun-83	13-May-01	6
Japan	Parliamentary	02-Jan-80	18-Dec-83	09-Nov-03	7
Korea	Presidential	01-Jan-88	18-Dec-92	19-Dec-02	3
Mexico	Presidential	01-Jan-88	21-Aug-94	02-Jul-00	2
Netherlands	Parliamentary	01-Jan-80	08-Sep-82	22-Jan-03	7
New Zealand	Parliamentary	02-Jan-87	27-Oct-90	27-Jul-02	5
Norway	Parliamentary	01-Jan-80	08-Sep-85	10-Sep-01	5
Poland	Parliamentary	01-Jan-93	21-Sep-97	23-Sep-01	2
Portugal	Parliamentary	04-Jan-88	06-Oct-91	17-Mar-02	4
Spain	Parliamentary	01-Jan-80	28-Oct-82	14-Mar-04	7
Sweden	Parliamentary	01-Jan-80	19-Sep-82	15-Sep-02	7
Switzerland	Parliamentary	02-Jan-80	23-Oct-83	19-Oct-03	6
Turkey	Parliamentary	04-Jan-88	20-Oct-91	03-Nov-02	4
United Kingdom	Parliamentary	01-Jan-80	09-Jun-83	07-Jun-01	5
United States	Presidential	01-Jan-80	06-Nov-84	02-Nov-04	6
Total					134

Note: The first column lists all of the 27 OECD countries included in our sample. The relevant type of election and the date from which daily stock prices for the respective MSCI Country Indices became available in Datastream are given in the following two columns. For any given country, the first election included is the earliest election that took place at least 500 trading days after the index starting date. This sample selection requirement allows estimating the volatility benchmark model. The date of the last election included corresponds to the most recent election that was held before the end of 2004.

Table 3.2: Descriptive Statistics

Variable	Mean	Std. Dev.	25^{th} Pctl.	Median	75^{th} Pctl.
Parliamentary	0.9179	0.2755	1.0000	1.0000	1.0000
Minority_Government	0.2463	0.4325	0.0000	0.0000	0.0000
Margin_of_Victory	−0.0281	0.2126	−0.1593	−0.0560	0.0592
Number_of_Parties	2.2015	1.2965	1.0000	2.0000	3.0000
Δ *Orientation*	0.3209	0.4686	0.0000	0.0000	1.0000
Early_Election	0.4179	0.4951	0.0000	0.0000	1.0000
Compulsory_Voting	0.2090	0.4081	0.0000	0.0000	0.0000
Ln_Population	16.8395	1.1945	15.8873	16.5974	17.8599
Ln_GDP_per_Capita	9.7472	0.5781	9.5720	9.8729	10.0955

Note: Descriptive statistics for a set of variables that are likely to influence election-induced volatility are reported above: Mean, Standard Deviation, 25^{th}, 50^{th} (Median), and 75^{th} Percentiles. The data set consists of 134 elections held in 27 OECD countries. *Parliamentary* is a dummy variable which takes a value of 1 for parliamentary elections and 0 for presidential elections. *Minority_Government* is a dummy variable which takes a value of 1 if the government fails to hold a majority of seats in parliament and 0 otherwise. *Margin_of_Victory* is defined as the difference between the percentage of votes obtained by government and opposition for parliamentary elections and the corresponding difference between winner and runner-up for presidential elections. *Number_of_Parties* denotes the number of independent political parties involved in the government in parliamentary systems and takes a value of 1 for presidential systems. Δ *Orientation* is a dummy variable which takes a value of 1 for a change in the political orientation of the government and 0 otherwise. *Early_Election* takes a value of 1 when elections are called before time and 0 otherwise. *Compulsory_Voting* takes a value of 1 if a given country has mandatory voting laws and 0 otherwise. *Ln_Population* and *Ln_GDP_per_Capita* are the natural logarithms of total population and GDP per capita (in constant 2000 US$) in a given country-year, respectively.

Table 3.3: Cumulative Abnormal Volatility around Election Day

Event Window	$CAV(n_1, n_2)$	Implied Percentage Change	Theoretical p-Value	Bootstrap p-Value
Panel A: Symmetric Event Windows				
$(-2, 2)$	5.3675	107.3500	0.0000	0.0016
$(-5, 5)$	6.8504	62.2764	0.0000	0.0026
$(-10, 10)$	7.9387	37.8033	0.0000	0.0048
$(-25, 25)$	11.9437	23.4190	0.0000	0.0076
Panel B: Asymmetric Event Windows				
$(0, 2)$	5.3655	268.2750	0.0000	0.0000
$(0, 5)$	6.6115	132.2300	0.0000	0.0000
$(0, 10)$	7.2652	72.6520	0.0000	0.0018
$(0, 25)$	8.6725	34.6900	0.0000	0.0054

Note: The data set consists of 134 elections held in 27 OECD countries. Panel A of the table reports cumulative abnormal volatility (CAV) in windows centered on Election Day, whereas Panel B reports the results for asymmetric event windows. The implied percentage change in country-specific volatility relative to the benchmark is reported in the third column. Theoretical p-values come from a χ^2 test for the null hypothesis of no change in country-specific volatility. The last column reports bootstrap p-values obtained from the empirical distribution of $CAVs$ developed under the null, using 5,000 iterations.

Table 3.4: Determinants of Excess Volatility

Variable	Expected Sign	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
Intercept		0.1143*	0.1594	0.0526	0.0029	1.8998
		(0.0688)	(0.2385)	(0.2449)	(0.2495)	(1.8072)
Margin_of_Victory	−	−0.6697**	−0.6793**	−0.7462**		−0.7702**
		(0.3300)	(0.3411)	(0.3527)		(0.3538)
Parliamentary			−0.0494	−0.2115	−0.1713	−0.2990
			(0.2528)	(0.2740)	(0.2719)	(0.3414)
Early_Election	+			0.0892	0.1376	0.1003
				(0.1403)	(0.1418)	(0.1478)
Δ *Orientation*	+			0.3229**	0.3805***	0.2997**
				(0.1430)	(0.1431)	(0.1482)
Compulsory_Voting	−			−0.3145**	−0.2176	−0.3651**
				(0.1550)	(0.1556)	(0.1701)
Number_of_Parties	+			0.0811	0.0397	0.0933
				(0.0582)	(0.0552)	(0.0578)
Minority_Government	+				0.2675*	
					(0.1608)	
Ln_Population	−					−0.0356
						(0.0679)
Ln_GDP_per_Capita	−					−0.1213
						(0.1221)
Adjusted R^2		2.56%	1.85%	6.08%	4.93%	5.52%

Note: This table presents results of regressions linking election-induced volatility to several explanatory variables. The dependent variable is a natural logarithm of the volatility ratio, defined as a quotient of the return variance computed over the $(-25, 25)$ event window and the variance of returns in a pre-event window of equal length, i.e. $(-76, -26)$. Heteroskedasticity-consistent standard errors of White (1980) are given in parentheses. The data set consists of 134 elections held in 27 OECD countries. *Margin_of_Victory* is defined as the difference between the percentage of votes obtained by government and opposition for parliamentary elections and the corresponding difference between winner and runner-up for presidential elections. *Parliamentary* is a dummy variable which takes a value of 1 for parliamentary elections and 0 for presidential elections. *Early_Election* takes a value of 1 when elections are called before time and 0 otherwise. Δ *Orientation* is a dummy variable which takes a value of 1 for a change in the political orientation of the government and 0 otherwise. *Compulsory_Voting* takes a value of 1 if a given country has mandatory voting laws and 0 otherwise. *Number_of_Parties* denotes the number of independent political parties involved in the government in parliamentary systems and takes a value of 1 for presidential systems. *Minority_Government* is a dummy variable which takes a value of 1 if the government fails to hold a majority of seats in parliament and 0 otherwise. *Ln_Population* and *Ln_GDP_per_Capita* are the natural logarithms of total population and GDP per capita (in constant 2000 US$) in a given country-year, respectively. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3.5: Change in Unconditional Variance

Event Window	Event Variance	Pre-Event Window	Pre-Event Variance	Percentage Change	Wilcoxon Signed-Rank Test	Fisher Test
Panel A: Symmetric Event Windows						
$(-2, 2)$	0.0166	$(-7, -3)$	0.0104	58.8283	2.9081***	397.54***
$(-5, 5)$	0.0165	$(-16, -6)$	0.0112	47.9641	5.4088***	498.43***
$(-10, 10)$	0.0159	$(-31, -11)$	0.0132	20.6038	2.9015***	559.09***
$(-25, 25)$	0.0158	$(-76, -26)$	0.0138	14.2509	2.3107**	908.30***
Panel B: Asymmetric Event Windows						
$(0, 2)$	0.0138	$(-3, -1)$	0.0068	103.4263	2.8460***	388.73***
$(0, 5)$	0.0166	$(-6, -1)$	0.0106	56.1312	3.4234***	418.39***
$(0, 10)$	0.0164	$(-11, -1)$	0.0123	33.5528	3.9053***	451.58***
$(0, 25)$	0.0161	$(-26, -1)$	0.0134	20.1656	2.8748***	610.43***

Note: This table reports the change in unconditional variance calculated for 134 elections held in 27 OECD countries. Panel A of the table reports unconditional variances in windows centered on Election Day, whereas Panel B reports the results for asymmetric event windows. In any row of the table, the event and pre-event windows have equal length. The event and pre-event variance denote the geometric averages of the unconditional variance estimators computed for all elections. The fifth column reports the percentage increase in average unconditional variance relative to its pre-event level. The Wilcoxon signed-rank test statistic follows a standard normal distribution under the null hypothesis of no change in variance. Given the validity of the null, the Fisher test statistic is χ^2 distributed with 268 degrees of freedom. *** and ** denote statistical significance at the 1% and 5% level, respectively.

Table 3.6: Cumulative Abnormal Returns around Election Day

Event Window	$CAR(n_1, n_2)$ in %	t-Statistic	p-Value	RRA Coefficient
Panel A: Symmetric Event Windows				
$(-2, 2)$	0.2283	0.4865	0.6274	3.9980
$(-5, 5)$	0.5480	0.9937	0.3221	4.2057
$(-10, 10)$	0.1699	0.2580	0.7968	1.5848
$(-25, 25)$	0.3297	0.3456	0.7302	1.5696
Panel B: Asymmetric Event Windows				
$(0, 2)$	−0.2512	−0.9123	0.3632	−2.2143
$(0, 5)$	−0.3187	−1.1960	0.2338	−0.7994
$(0, 10)$	−0.3738	−1.1421	0.2555	−0.7150
$(0, 25)$	0.3182	0.4830	0.6299	1.9644

Note: This table reports cumulative abnormal returns ($CARs$) calculated around 134 elections held in 27 OECD countries. Panel A of the table reports $CARs$ in windows centered on Election Day, whereas Panel B reports the results for asymmetric event windows. CAR is defined as the average excess return on the election country index over the MSCI World Index, cumulated over time. The t-statistics with the corresponding p-values are calculated for the null hypothesis of no compensation for the election risk. The RRA coefficient denotes the break-point level of the constant relative risk-aversion coefficient above which the strategy of international portfolio diversification yields higher expected utility than the strategy of investing in election countries.

Table 3.7: Implied Volatility Indices

Country	Datastream Code	Index Start Date	First Election Included	Last Election Included	Number of Elections
Austria	ATXC.SERIESC	21-Jul-99	03-Oct-99	24-Nov-02	2
Czech Republic	CTXC.SERIESC	16-Feb-00	14-Jun-02	14-Jun-02	1
France	CACLC.SERIESC	05-Jan-00	09-Jun-02	09-Jun-02	1
Germany	DAXC.SERIESC	19-Jul-99	22-Sep-02	22-Sep-02	1
Japan	JPNC.SERIESC	10-Mar-00	25-Jun-00	09-Nov-03	2
Mexico	MEXC.SERIESC	10-Mar-00	02-Jul-00	02-Jul-00	1
Netherlands	EOEC.SERIESC	24-Aug-99	15-May-02	22-Jan-03	2
Poland	PTXC.SERIESC	16-Feb-00	23-Sep-01	23-Sep-01	1
Switzerland	SMIC.SERIESC	01-Mar-00	19-Oct-03	19-Oct-03	1
United Kingdom	LSXC.SERIESC	05-Jan-00	07-Jun-01	07-Jun-01	1
United States	ISXC.SERIESC	11-Aug-99	07-Nov-00	02-Nov-04	2
Total					15

Note: The first column lists all of the 11 sample countries that have implied volatility indices available in Datastream. The second column provides the relevant Datastream code, and the third one indicates the series starting date. The dates of the first and last election included as well as the total number of elections for each of the sample countries are reported in the following columns.

Chapter 4

Institutional Investors and Stock Market Efficiency

4.1 A Decreasing January Effect and the Impact of Institutional Investors

4.1.1 Motivation and Literature Review

Since the late 1970s, researchers have discovered several seasonal patterns in stock returns that constitute a challenge to the efficient markets hypothesis (Fama (1970)). Regularities in stock returns or stock market anomalies comprise, among many others, the January effect, the Monday seasonal, and the size effect. In this chapter, we focus on the following aspect of stock market anomalies: If stock returns exhibit exploitable regularities, then smart traders are expected to take advantage of these patterns, thereby earning abnormal profits. Consequently, on stock markets with a sufficiently large number of smart traders, anomalies are supposed to disappear as the trading of this investor group arbitrages away seasonal patterns in stock returns.

Recent empirical findings suggest that institutional investors play the role of smart traders on stock markets and, therefore, may have an impact on stock market anomalies. Institutional investors can be characterized as informed traders who speed up the adjustment of stock prices to new information, thereby rendering the stock market more efficient. Institutions can obtain an informational advantage by exploiting economies of scale in information acquisition and processing. The marginal costs of gathering and processing information are lower for institutional than for individual traders. In addition, institutional investors may be better trained and have superior resources than individual investors. Moreover, for many years it has been common practice of companies to inform securities analysts in advance about company-specific news, and only recently regulatory measures have been launched (namely the SEC's Regulation FD[1]) to prevent this habit. Hence, institutional investors' trading decisions may be stronger information-driven than those of individual investors.

Dennis and Weston (2001) support this view by providing evidence for U.S. stock exchanges that institutions are better informed than individual investors. Cohen, Gompers, and Vuolteenaho (2002) show that institutional investors push stock prices towards their fundamental values by exploiting individual traders' sentiment. Following Barber and Odean (2008), individual investors display attention-based buying behavior, whereas institutions do not exhibit this kind of non-fundamental trading pattern.

The impact of institutional trading on stock market anomalies has recently been covered by three papers. Kamara (1997) and Chan, Leung, and Wang (2004) highlight the role of institutional investors on the Monday seasonal. They present evidence for U.S. stock markets that an increase in institutional ownership decreases the magnitude of the Monday effect. Gompers and Metrick (2001) show that an increase in institutional trading is partly responsible for the disappearance of Banz (1981)' small stock premium.[2]

In this study, we focus on the impact of institutional trading on a third major anomaly, namely the January effect (Rozeff and Kinney (1976), Reinganum (1983), Gultekin and Gultekin (1983), and Ritter (1988)).[3] Two of the most prominent explanations for the January effect refer to the specific trading behaviors of individual and institutional investors. First, the tax-loss-selling hypothesis explains the January anomaly with tax-motivated trading of individual investors. As the end of the year approaches, individual investors sell stocks that declined in value in order to realize tax losses. After the turn of the year they re-invest in these securities, which pushes

[1] On August 15, 2000, the U.S. Securities and Exchange Commission (SEC) adopted Regulation FD to address the selective disclosure of information by publicly traded companies and other issuers. Regulation FD provides that when an issuer discloses material nonpublic information to certain individuals or entities–generally, securities market professionals, such as stock analysts, or holders of the issuer's securities who may well trade on the basis of the information–the issuer must make public disclosure of that information. In this way, the new rule aims to promote the full and fair disclosure.

[2] Another strand of the finance literature views institutions as investors which induce non-fundamental dynamics in stock returns due to their specific trading behavior. The main arguments in this context are investment activities relying on herding, positive feedback trading, and window-dressing strategies (Lakonishok, Shleifer, and Vishny (1992), Grinblatt, Titman, and Wermers (1995), Nofsinger and Sias (1999), Badrinath and Wahal (2002), and Griffin, Harris, and Topaloglu (2003)).

[3] The *January Effect* refers to systematically higher stock market returns in January than in the remaining months of the year. This anomaly should not be confused with what has become known as the *Other January Effect* in the literature (see, e.g., Cooper, McConnell, and Ovtchinnikov (2006)): the predictive power of January returns for market returns over the next 11 months of the year. The Other January Effect is not the subject of this thesis.

stock prices up (Ritter (1988)). Second, the window-dressing hypothesis suggests that institutional investors' portfolio rebalancing activities are responsible for the January anomaly. Institutions are evaluated relative to their peers and, therefore, buy winners and sell losers in order to present respectable year-end portfolio holdings (Lakonishok, Shleifer, Thaler, and Vishny (1991)). The findings in Sias and Starks (1997) are favorable for the tax-loss-selling hypothesis and show that individual traders are primarily responsible for the January anomaly.

This study highlights the impact of institutional traders on the January effect in Poland and Hungary. The history of both emerging stock markets provides a unique institutional environment to investigate the influence of individual and institutional investors on the January anomaly. In Poland, the pension system reform on May 19, 1999, separates the history of the stock market into a period of predominantly individual trading and a period of increased institutional trading. Similarly, in Hungary, private pension funds were founded in 1997 and started their financial activities in 1998. Before 1998, primarily small individual investors populated the Hungarian stock market.

The pension system reform in both countries changed the investor structure due to the enrichment of the old pay-as-you-go system with a privately managed pension funds pillar. Since 1999, pension funds have become an important group of institutional investors on the Polish and Hungarian stock markets. In addition to the change of the investor structure, in both countries capital gains taxes do not exist, thus excluding the tax-loss-selling hypothesis as a rationale for the January effect. Consequently, if a January effect can be detected in the data during the period before the entrance of pension fund investors in both stock markets, then it must be driven by an anomalous trading behavior of Polish and Hungarian individual investors. We exploit the increased institutional ownership in both emerging capital markets to provide evidence on the impact of individual and institutional investors' trading decisions on the January anomaly.

Relying on the institutional background of the Polish and the Hungarian stock markets, we contribute to the literature answering the following two questions. First, is there evidence in favor of a January effect during the period of individual trading? If this is the case, we can conclude that individual investors' non-fundamentally driven trading decisions led to the January anomaly. Second, in which way did Polish and Hungarian pension fund investors contribute to the January anomaly after 1999 and 1998, respectively? In case pension funds exhibit window-dressing behavior, we expect a strengthening effect on the January anomaly. In contrast, if pension funds' trading decisions are more influenced by fundamental information, a dampening effect on unusually high stock returns in January can be expected.[4]

The remainder of this section proceeds as follows. Subsection 4.1.2 outlines the institutional background for Poland and Hungary. Subsection 4.1.3 introduces the data set, Subsection 4.1.4 describes the econometric methodology, and Subsection 4.1.5 contains the empirical findings. Subsection 4.1.6 provides robustness checks, and Subsection 4.1.7 summarizes and concludes.

4.1.2 Institutional Background

4.1.2.1 Poland

Re-established in 1991, the Polish stock market has grown rapidly during the last decade in terms of both the number of companies listed and market capitalization. In comparison to the two other European Union accession countries in the region, namely the Czech Republic and Hungary, the capitalization of the Polish stock market is significantly higher. It is comparable to that of the smaller mature European stock markets like Austria and reached approximately 60 billion US$ at the end of 2004 (WSE (2005)).

The change in the investor structure on the Polish stock market has its origin in the pension system reform. In 1999, the public system was enriched by a private component, represented by open-end pension funds. Participation in this component, often called the "second pillar", is mandatory for employees below certain age. They are obliged to transfer 7.3% of their gross salary to the government-run social insurance institute called Zakład Ubezpieczeń Społecznych (ZUS), which in turn transfers the collected contributions to the pension funds.[5] The first transfer of money from the ZUS to the pension funds took place on May 19, 1999. This date marks a change of

[4] It is obvious that the date of entrance of pension funds into the stock market plays an important role in the following investigation. Similarly, one branch of the literature studies the impact of the introduction of futures markets on stock return anomalies of the spot market underlying (Kamara (1997), Szakmary and Kiefer (2004)). In our investigation, we can exclude an influence from the introduction of futures markets because these markets were established earlier (January 16, 1998, in Poland and March 31, 1995, in Hungary) than the appearing of pension fund investors on the stock markets took place. Nevertheless, we acknowledge that there may be other possible explanations for the decreasing January effect, like an ongoing efficiency with increased integration of transition economies (Rockinger and Urga (2001)). We control for this influence and provide empirical evidence in Subsection 4.1.6.

[5] For a more detailed description of the Polish pension system and for further references see Voronkova and Bohl (2005).

the investor structure on the Polish stock market. In 1999, about 20% *domestic institutional* investors and 45% *domestic individual* investors traded at the Warsaw Stock Exchange. Over time the proportion of domestic institutional traders has increased, whereas the relative importance of individual investors has decreased. In 2004, approximately one-third of the investors were domestic individuals, and about one-third were national institutions. Constantly about one-third of the investors on the Polish stock market adhere to the group of *foreign* investors.

While before May 19, 1999, the majority of traders were small, private investors, after that date pension funds became an important group of institutional investors on the stock market in Poland. There were also some mutual funds active in the market, but they had relatively small amounts of capital under management. Moreover, the role of corporate investors, i.e., companies investing their capital surpluses, was very small. This unique institutional characteristic allows us to compare the period before May 19, 1999—characterized by predominantly non-institutional trading—with the period after that date, when pension funds as institutional investors started to act on the stock market.

The number of pension funds in the 1999–2003 period varied between 15 and 21. The change in their number occurred mainly due to some acquisitions of smaller funds by larger ones. It is important to note, however, that their structure as well as the structure of the assets under their management remained invariant. By the end of 2003, 17 pension funds operated in the Polish stock market with about 12 billion US$ under management. In comparison, Polish insurance companies and mutual funds had only 3 and 1 billion US$ of assets, respectively. In 2003, pension funds invested about 4 billion US$ in stocks listed on the Warsaw Stock Exchange. Their stock holdings predominantly consist of large-capitalization stocks that are listed in the blue-chip index WIG20 and usually belong to the Top 5 in their industries.

Concerning capital gains taxation, in Poland the following regulations were in force:[6] Until the end of 2003, capital gains from the sale of shares were tax-exempt for domestic individual investors. Since January 1, 2004 capital gains of this type have been taxed at a flat rate of 19%. For corporations, capital gains have consistently been treated as part of the company's profits and therefore been taxed at the regular corporate income tax rate. Polish pension fund investors are tax-exempt. Div-

[6] For detailed information, see Ernst & Young (2006a), Ernst & Young (2006b), PricewaterhouseCoopers (2006a), and PricewaterhouseCoopers (2006b).

idend withholding taxes varied over the period under review, the latest rate being 19% (effective 2004). However, the number of firms paying dividends is low.

4.1.2.2 Hungary

The Budapest Stock Exchange, re-established in 1990, experienced a significant increase in its capitalization, attaining about 6 billion US$ in 1996, mainly due to the privatization of Hungary's bigger state-owned companies such as Mol, OTP, Gedeon Richter, and Matav. In the following years, the stock market went through a phase of continuous growth, reaching a capitalization of 30 billion US$ at the end of 2004.

The introduction of a three-pillar pension system on January 1, 1998, had an influence on the Hungarian stock market because a growing share of households' savings was channeled to stock market investments through pension funds. Since 1998, individuals can choose between the mandatory public system—the first pillar—and the mandatory private system. Open-end private mandatory pension funds represent the second pillar of the Hungarian pension system. The first 38 mandatory private funds started their activities in 1998 with 134 million US$ of assets under management and about 1.3 million members. The third pillar consists of voluntary pension funds, which can be both open-end and closed-end funds and also play an important role with a comparable amount of assets.[7]

The establishment of the private mandatory pension funds in 1998 was beneficial and stimulating for voluntary pension funds. The year 1998 can therefore be considered as the year when pension funds appeared as institutional investors on the Hungarian stock market. However, compared to the institutional framework in Poland, the exact date of entrance of pension funds into the Hungarian stock market is less clear-cut and hardly traceable. Whereas for Poland May 19, 1999, is known as the start date of pension funds' investment activities and well-documented as such, the investment activities of Hungarian pension funds seemed to develop gradually over the year 1998. Detailed information on this issue is practically not available. Consequently, we choose January 1, 1999, as the start date of increased institutional ownership on the Hungarian stock market to ensure that the entire post-event period is characterized by institutional trading activities. The pension funds' capital was growing during the following years and, by the end of 2004, amounted to 4 and 2.5 billion US$ for the mandatory and voluntary pension funds, respectively.

[7] The first voluntary pension funds started their activity already in 1994. However, the assets under their management were marginal at that time.

The number of pension funds decreased over time, mainly due to acquisitions, and by the end of 2004, 18 private and 75 voluntary pension funds remained in the market. Contrary to other countries, where pension funds participate directly in the stock market, in Hungary an increasing number of pension funds entrusted their assets to investment fund managers. Consequently, the impact of pension funds on stock market prices should be evaluated by means of portfolio managers' investment activities. At the end of 2004, 23 investment fund managers had under their management 4.9 billion US$ of pension fund assets, 5.2 billion US$ of investment fund assets, and 3.7 billion US$ of contributions from other sources. Notwithstanding the assignment of pension funds' assets to portfolio managers, their investment activities have to adhere to the pension funds' investment regulations specified by law. In addition, the accumulated accounts can be invested in the longer term since contributions are not accessible before retirement.

In Hungary, capital gains realized by individual investors on the domestic or any other European Union stock exchange were considered as non-taxable interest-type income during our sample period.[8] Capital gains on transactions not qualified as stock exchange deals are, however, subject to tax at a top tax rate of currently 25%. Only for a short period of time (2001–2002), stock market gains were also taxed at the then applicable uniform 20% capital gains tax rate. For corporate investors, capital gains are included in taxable income and taxed at standard rates. While inter-company dividend payments are tax-exempt, the dividend withholding tax rate for individual recipients varied, current rates being flat at either 25% or 35% (effective 2005). Pension funds are not subject to tax on the proceeds of the funds; these are only taxed once they are paid out to contributors.

4.1.3 Data

Poland. The data for Poland contain daily closing prices for all stocks listed on the Warsaw Stock Exchange in the period from October 3, 1994 to March 31, 2004.[9] These

[8] As of September 1, 2006, a 20% capital gains tax rate applies in this case. For more detailed information on capital gains taxation, see Ernst & Young (2006a), Ernst & Young (2006b), PricewaterhouseCoopers (2006a), and PricewaterhouseCoopers (2006b).

[9] The selection of the start date is due to the following reasoning. Shortly after its re-opening, the Polish stock market experienced a stock price increase of 924% from May 6, 1993 to March 8, 1994, and a subsequent crash. Furthermore, it was not until October 3, 1994, that trading on the Warsaw Stock Exchange was extended from four days to five days a week. Starting our inquiry at the beginning of October 1994 ensures that the empirical findings are neither distorted by the bubble and crash periods nor affected by the change in trading frequency.

time series were directly provided by the Warsaw Stock Exchange (WSE). Altogether, the sample comprises 278 firms over the indicated sample period. The time series are stock-split adjusted and corrected for outliers to assure that our results are not driven or distorted by few extreme values. For this purpose, the 0.5% of highest and lowest returns observed in the data set are excluded from the investigation and, therefore, deleted from all subsamples.

To investigate the impact of the pension funds' investment activities, we construct two subsamples of actively institutionally traded stocks as follows. We calculate a measure of each stock's institutional coverage by dividing the aggregate pension fund holdings of that stock by the overall aggregate pension fund holdings in a particular year. This measure can be interpreted as the percentage share of a particular stock in the aggregate pension fund holdings. A stock is defined as actively institutionally traded in a given year if the measure of relative institutional holdings exceeds 1%.[10]

We calculate this measure for all stocks and all years separately during the 1999–2003 period and end up with five yearly measures of relative pension fund holdings for each individual stock. A stock is included in the first sample of actively institutionally traded stocks if the pension fund holding measure of this stock exceeds the 1% level in at least three out of the five years. This amounts to 60% of the post-event period. In an alternative, less strict definition a stock has to exceed the 1% cut-off point in at least two of the five years, i.e., during 40% of the post-event period. These criteria result in the identification of 20 stocks for the stricter definition and 28 stocks for the less strict definition of institutionally traded shares. Columns 1 and 2 of Table 4.1 provide additional information about these stocks. Whereas Polish pension fund investors do not have a preference for stocks of a specific sector, they concentrate their investments on large firms' stocks.

[Insert Table 4.1 here]

Hungary. For Hungary, the data consist of daily closing prices for the stocks listed on the Budapest Stock Exchange in the period from January 3, 1994 to December 31, 2004. The time series were obtained from Thomson Financial Datastream. Altogether,

[10] We drop stocks with only marginal institutional coverage as for these stocks institutional trading behavior may not have a large impact on stock returns. The 1% cut-off point is arbitrarily chosen but proved to be an acceptable compromise for the purpose of our study. On the one hand, it allows us to eliminate those stocks which are not at all or only marginally covered by institutional investors and to come up with a limited number of stocks that are actively traded by institutions. On the other hand, the size of the resulting subsamples is still sufficient for econometric testing.

the cross-section of the sample comprises 84 firms. The same trimming procedure was applied to the data set as described above for the Polish case. In contrast to Poland, we do not have reliable information regarding stock splits, dividends, and other impact factors on stock returns. This provides an additional reason for the exclusion 0.5% of the extreme stock return observations in both tails of the distribution.

To determine a subsample of institutionally traded stocks for the Hungarian stock market, we requested the portfolio holdings of all Hungarian pension funds. The pension funds' replies show that their stock market investment decisions closely mirror the composition of the main stock index BUX. In the sample of Hungarian stocks actively traded by institutional investors, we therefore focus on the stocks included in the BUX. Information on the BUX composition was provided by the Budapest Stock Exchange (BSE) for the 1996–2004 period. Contrary to Poland, we do not use a 1% cut-off criterion because the BUX is dominated by very few stocks with high weights. Hence, a cut-off point as the one mentioned above would considerably reduce our sample in size. The number of stocks included in the institutional sample would be too small to conduct a cross-sectional investigation.

For a strict definition of institutionally traded stocks that is roughly in line with the selection criterion for Poland, we use all stocks that are included in the BUX for at least 60% of the time in the post-reform sample period 1998–2004. This definition results in the identification of 17 institutionally traded stocks. For a less strict definition, we require inclusion in the BUX for at least 40% of the same time period. The less strict definition increases the sample of institutionally traded stocks to 19. We use these two subsamples of 17 and 19 stocks to investigate the effect of institutional trading on the Hungarian stock market. Columns 3 and 4 of Table 4.1 list the Hungarian companies selected together with their sector affiliation.

4.1.4 Methodology

4.1.4.1 Groupwise Regressions

In the empirical investigation we distinguish between the impact of predominantly individual versus increased institutional ownership on stock returns in January. First, the hypothesis is investigated that individual investors exhibit anomalous trading behavior and cause abnormally high stock returns in January. Second, we analyze the hypothesis that institutions are informed traders relying on fundamental information and, consequently, the entrance of pension funds on the stock market dampens the anomalous January effect.[11] If the contrary holds, the trading behavior of pension funds can be ascribed a positive contribution to higher stock returns in January relative to other months of the year, which would be in line with the window-dressing hypothesis.

The hypotheses are investigated within a panel framework and separately tested for different subsamples of stocks from Poland and Hungary. The look beyond aggregate index data proves beneficial since we can exploit the richer information in the cross-section of returns. The advantages of a panel data model over a purely time-series investigation of index data or individual shares are manifold (see, e.g., Baltagi (2005)). Most importantly, unobserved individual heterogeneity can be controlled for that would otherwise have to go undetected and could generate biased results. Specifically, the following one-way error component regression model is run:

$$r_{i,t} = \beta_0 + \beta_1 JAN_t + \beta_2 JAN_t^{Post} + \beta_3 r_{i,t-1} + u_i + e_{i,t}, \tag{4.1}$$

where the subscript i denotes the cross-sectional and t the time-series dimension of the data set. The dependent variable is the daily stock return $r_{i,t}$, calculated as the logarithmic difference in prices, $r_{i,t} = 100 \ln(P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ denotes the individual stock price at the close of every trading day.

JAN_t is a dummy variable which takes on the value of 1 in January throughout the whole sample period (0 otherwise). The dummy variable JAN_t^{Post} is 1 only for those January observations that fall into the post-pension system reform period, i.e., beginning with January 2000 for Poland and January 1999 for Hungary (0 otherwise). In addition, we allow for stock returns autocorrelation in the time-series dimension by including the lagged dependent variable $r_{i,t-1}$ as an additional explanatory variable.[12] u_i denotes an unobservable stock-specific random effect. $e_{i,t}$ is the remainder disturbance. Assumptions made by the error-component model are that $u_i \sim N(0, \sigma_u^2)$ and $e_{i,t} \sim N(0, \sigma_e^2)$, and that the individual error components u_i and $e_{i,t}$ are neither

[11] The Polish pension system reform, the associated increase in institutional trading, and its implications for market efficiency/stabilization have been investigated with different foci in previous literature: Bohl, Brzeszczyński, and Wilfling (2008) and Bohl and Brzeszczyński (2006) examine stock return volatility, Gębka, Henke, and Bohl (2006) return autocorrelation, and Voronkova and Bohl (2005) scrutinize the investment behavior of pension funds.

[12] In panels with a short time dimension the presence of lagged dependent variables causes inconsistent and biased estimates. However, in our case T is quite large so that the bias resulting from the presence of a lagged dependent variable can be neglected (Judson and Owen (1999), Baltagi (2005)).

correlated with each other nor autocorrelated across both cross-section and time-series units.[13]

In the above specification, a positive and significant parameter β_1 provides evidence in favor of a January effect in stock returns. For the interpretation of the parameter β_2, three cases have to be distinguished: First, a negative and significant coefficient β_2 indicates a reduction of positive January stock returns (estimated by $\hat{\beta}_1$) due to the entrance of pension funds as institutional investors into the market. Second, if β_2 is positive and significant, then institutional investors' trading behavior is in line with the window-dressing hypothesis because a strengthening of the January anomaly can be observed. Third, if β_2 is statistically insignificant, institutions do not have an influence on the January anomaly. The sum $(\beta_1 + \beta_2)$ provides a measure of the magnitude of the January effect in the period of increased institutional trading.

4.1.4.2 Joint Estimation

In addition to testing the hypotheses separately for the four different subsamples described above, we estimate the following joint model with interaction variables:

$$\begin{aligned} r_{i,t} = \beta_0 &+ \beta_1(JAN_t \times INST_i) + \beta_2(JAN_t^{Post} \times INST_i) \\ &+ \beta_3 INST_i + \beta_4 POST_t + u_i + e_{i,t}, \end{aligned} \tag{4.2}$$

where all previously introduced variables are defined as in Equation (4.1).[14] In addition, the indicator variable $INST_i$ equals 1 for those companies included in the sample of institutionally traded stocks and is 0 otherwise. $POST_t$ is a dummy variable with value 1 for the period of increased institutional trading and 0 otherwise. The interaction variables $(JAN_t \times INST_i)$ and $(JAN_t^{Post} \times INST_i)$ correspond to JAN_t and JAN_t^{Post} in Equation (4.1) when it is estimated for the institutional subsamples.

The model specified above is estimated for both subsamples of institutionally traded stocks. We henceforth refer to the version estimated with the more strictly defined institutional dummy $INST_i$ as Equation (4.2a) and to the less strictly defined variant as Equation (4.2b). The coefficients β_1 and β_2 can be interpreted as described for Equation (4.1). In addition, β_3 captures possible systematic differences between average stock returns of the institutional and the control sample, and β_4 displays

[13] The model selection is supported by Hausman specification tests (Hausman (1978)). We also test for serial correlation in the error distribution with Lagrange-multiplier (LM) tests (Breusch (1978), Godfrey (1978)).

[14] The lagged dependent variable is dropped from the regressor list for the sake of brevity since its inclusion did not alter the empirical findings.

aggregate factors that affected average stock returns over time in the same way for institutionally traded and non-traded shares.

4.1.5 Empirical Findings

4.1.5.1 Summary Statistics

All results are presented separately for the two subsamples of stocks actively traded by institutional investors, a control sample of all stocks excluding the stocks identified as institutionally traded as well as the whole sample reflecting the entire Polish and Hungarian stock markets. Hence, we are able to analyze the impact of the Polish and Hungarian pension system reform on stock returns not only through time—before and after the pension funds' appearance as institutional traders on the stock market—but also in a cross-sectional dimension, i.e., among stocks more actively traded and those nearly non-traded by institutional investors.

To gain some first insight into the seasonal patterns inherent in our data, daily average stock returns for January and for February to December are reported in Table 4.2. Daily mean stock returns in January are positive and higher than average stock returns between February and December for all samples. Furthermore, for both institutional subsamples (Panels A1, B1, A2, B2) we observe higher average January stock returns during the 1994–1999 (1994–1998) period relative to the years 2000–2004 (1999–2004) for Poland (Hungary). This also refers to the whole samples (Panels D1, D2) which include all stocks listed on the respective stock exchange. Interestingly, for the Polish control sample (Panel C1) we observe an increase of average stock returns over time, whereas Hungarian stock returns (Panel C2) are slightly lower in the 1999–2004 period compared to the 1994–1998 subsample.

[Insert Table 4.2 here]

4.1.5.2 Regression Results

Poland. Table 4.3 displays the results from estimating regression (4.1) for Poland. When looking at the outcomes for the two subsamples of actively institutionally traded stocks (Panels A and B), we find evidence in favor of a pronounced January effect in the period when the Polish stock market was dominated by individual investors. The estimated coefficients of the January effect are about 0.36. All coefficient estimates of the dummy variable JAN_t are statistically significant at the 1% level. The empirical findings in favor of a January effect are insofar interesting as during the period of predominately individual trading capital gains taxes did not exist in Poland. Hence, the tax-loss-selling hypothesis can be ruled out as a rationale for higher stock returns in January. We can therefore conclude that Polish stock returns dynamics exhibit an anomalous January effect during the period prior to the entrance of institutional investors, which may be explained by individual investors' sentiment.[15]

[Insert Table 4.3 here]

Moreover, for both institutional samples the magnitude of the January effect decreases in the period after the pension fund investors' entrance into the stock market, measured by the coefficients of the post-reform dummy JAN_t^{Post}. The estimated parameter values are statistically significant and about -0.22. Thus, the significant negative parameter estimates of this institutional investors dummy lead us to reject the window-dressing hypothesis. The anomalous January effect in stock returns does not entirely disappear after the entrance of pension funds as institutional investors into the Polish stock market. However, its magnitude becomes substantially lower.

The results are robust towards the inclusion of the lagged dependent variable $r_{i,t-1}$. For both institutional samples, the coefficient of $r_{i,t-1}$ is positive and significant, which can be explained by the implications of strategic trading models (Kyle (1985), Barclay and Warner (1993)). Rational informed investors spread their trades over time to conceal information. By breaking up a large order into several smaller trades, institutional investors reduce the overall price impact. Moreover, price impacts may be inversely related to market liquidity (Madhavan and Smidt (1993)). This suggests that the benefits of trading over a longer horizon are greater in thin relative to liquid stock markets which, in turn, implies an increase in trade duration and a decrease in order size. Moreover, the significance of a lagged dependent variable may indicate predictability in stock returns and a violation of the efficient markets hypothesis.

The estimated results for the control sample (Panel C) consisting of all stocks except for the 28 institutionally traded ones reinforce the above findings. The coefficients of the dummy variable JAN_t are positive and significant at the 10% and 19% levels. Hence, we find at least weak evidence indicating that a January effect exists in returns of non-institutionally traded stocks. In contrast to the results for the two institutional

[15] The existence of a January effect in stock returns without capital gains taxes is not new. Tinic, Barone-Adesi, and West (1987) provide evidence for Canada and Jones, Pearce, and Wilson (1987) for the U.S. before capital gains were taxed in these countries.

samples, the parameters for JAN_t^{Post} are statistically insignificant. For stocks not actively traded by Polish pension fund investors, the magnitude of the January effect does not decrease during the period after May 19, 1999.[16] The statistically insignificant parameters for JAN_t^{Post} in the control sample emphasize that the estimated decrease in the two institutional samples is caused by the institutions' trading behavior and not by other factors.[17] In addition, the estimated coefficient of the variable JAN_t^{Post} for the whole market is not significant either, which suggests that the January effect for the market as a whole continues to be driven by individual investors.

The empirical findings of model (4.2) are reported in the bottom part of Table 4.3. The pronounced January effect for actively institutionally traded Polish stocks is confirmed, as is the substantial decrease in the anomaly's magnitude after the entrance of pension funds into the stock market. In addition, stocks actively traded by institutions earn significantly higher returns relative to the rest of the sample. The period of increased institutional trading is accompanied by higher average stock returns compared to the period before the pension system reform.

Hungary. The findings for Hungary in Table 4.4 are consistent with the ones for the Polish stock market and support the pension funds' impact on the January anomaly. The estimation results for the two subsamples of actively institutionally traded stocks (Panels A and B) show a pronounced January effect in the period before the investment activities of Hungarian pension funds. The estimated parameters of the dummy variable JAN_t are about 0.44 and are statistically significant. In line with the results for Poland, the tax-loss-selling hypothesis as a rationale for higher January stock returns can be ruled out because capital gains are not taxed in Hungary. Moreover, the anomalous January effect decreases drastically after the entrance of pension funds into the stock market with statistically significant coefficients for JAN_t^{Post} of about -0.36. The findings are robust concerning the inclusion of the lagged dependent variable. The estimated parameters are positive and significant, supporting the implications of

[16] Given the marginal level of significance of the JAN_t coefficients, we run separate regressions investigating whether a January effect exists in the post-event period. The values of the coefficients of the January dummy variables are slightly higher relative to the ones reported in Table 4.3 and are significant at the 1% level. Hence, a January effect exists in the period after May 19, 1999, in non-institutionally traded Polish stocks.

[17] The January effect in the pre-event period is substantially higher for institutionally traded stocks compared to the stocks in the control sample. A reason for this finding may be the extreme illiquidity of a subset of stocks in the control sample. As our study focusses on the evolution of January stock returns over time instead of the level of the January effect for particular stocks, we do not further explore this issue.

strategic trading models and market liquidity as well as considerations on the violation of the efficient markets hypothesis outlined above.

[Insert Table 4.4 here]

The empirical results of the control sample (Panel C) also indicate that a January effect exists in the period before Hungarian pension funds invested on the stock market. The estimated parameters of JAN_t are positive and significant at the 1% level. In line with the findings for Poland, the magnitude of the January effect is smaller for non-institutionally traded shares relative to stocks actively institutionally traded. More importantly, the estimated coefficients of the dummy variable JAN_t^{Post} are not statistically significant. This finding supports the hypothesis that the estimated decrease in the two institutional samples is caused by institutions' trading behavior and not by other factors. The decrease in the magnitude of the January effect is also observed for the whole market. Lastly, the estimation of regression model (4.2) supports the empirical results discussed above.

4.1.6 Robustness Checks

4.1.6.1 Control Variables

All results presented so far were calculated for a sample where 0.5% of extreme stock returns in both tails of the distribution were dropped. As a check of robustness, we repeated the above analysis using the sample without excluding the outliers. The results for Poland are qualitatively identical. The same holds for Hungary except for the findings of the control sample. For this subsample, very few large return outliers seem to impact the findings and justify our outlier correction.[18]

Furthermore, we tackle the objection that the compelling evidence in favor of a decreasing January effect brought by institutional investors might merely be a reflection of some common influence or trend. For instance, the dynamics of January returns in Poland and Hungary might be impacted by developments on the U.S. stock markets or simply be driven by a time trend towards increased efficiency, along with ongoing integration of the Eastern European transition economies with other already established markets. For this purpose, we widen the baseline regression model (4.1) to allow for a set of control variables:

$$r_{i,t} = \beta_0 + \beta_1 JAN_t + \beta_2 JAN_t^{Post} + \beta_3 r_{i,t-1} + \mathbf{c}'\mathbf{X}_t + u_i + e_{i,t}. \tag{4.3}$$

[18] The findings are not reported but available on request.

All constituents of Equation (4.3) are defined as previously. In addition, $\mathbf{c}'$ denotes a 1×3 vector of parameters, $\mathbf{c}' = (c_1, \ldots, c_3)$, and $\mathbf{X}_t$ is a 3×1 vector of control variables:

$$\mathbf{X}_t = \begin{pmatrix} r_{t-1}^{US} \\ TIME_t \\ VOL_t \end{pmatrix},$$

where

1. r_{t-1}^{US} is the one-period lagged return of the S&P 500 Index[19], calculated as the logarithmic difference in prices, $r_{t-1}^{US} = 100 \ln(P_{t-1}^{US}/P_{t-2}^{US})$;

2. $TIME_t$ is a linear time trend;

3. VOL_t is the logarithm of aggregate trading volume in the respective market on day t, compounded as $VOL_t = \ln(\sum_{i=1}^{n} VOL_{i,t})$, where n stands for the number of individual stocks.

Volume data were downloaded from Thomson Financial Datastream. Lagged U.S. stock returns are meant to capture international influences, whereas the latter two variables account for the development of the Polish and Hungarian stock markets over the decade investigated. Should the significant reduction in abnormal January returns be due to a common time trend or more active trading in general, we would expect such an evolution to be mirrored in significant coefficients for $TIME_t$ or VOL_t.

The results of this robustness check are displayed in Table 4.5. In general, the empirical findings are fairly insensitive towards the inclusion of the three control variables. The estimated coefficients of the January dummy JAN_t are positive and statistically significant in all cases at the 1% level. More importantly, the coefficients of the JAN_t^{Post} dummy variable are in the majority of cases negative and statistically significant at least at the 5% level, while two parameters are still significant at the 14% level. This finding is robust towards the inclusion of the control variables either individually or jointly.[20] Our main hypothesis that the decrease in the anomaly's magnitude is driven by the institutions' trading activities is confirmed.

[Insert Table 4.5 here]

[19] S&P stands for Standard and Poor's, a U.S. provider of stock market indices.

[20] We do, however, not bundle trading volume variables and the time trend together into one equation to avoid potential multicollinearity problems due to high positive correlation between these variables (0.91 for Poland and 0.53 for Hungary).

4.1.6.2 Rolling Regressions

Finally, we investigate whether the decrease in the magnitude of the January anomaly takes place gradually over a longer period or within a relatively short period of time. This question is relevant because it helps us to assess whether the observed results are really due to the appearance of institutional investors on the stock market. To accomplish this task, we use a rolling estimation window technique and run the regression:

$$r_{i,t} = \alpha + \beta JAN_t + u_i + e_{i,t}, \tag{4.4}$$

where all variables are defined as in Equation (4.1). Starting in October 1994 for Poland and in January 1994 for Hungary, we estimate this regression for a three-year time period and obtain a parameter estimate of β. This parameter is an estimate of the average January effect during the estimation period. Then we move the estimation window by one month toward the end of the sample and estimate regression (4.4) again. We end up with a time series of β estimates that can be plotted and subjected to visual investigation afterwards.

Last, we present the findings of the rolling estimation of Equation (4.4). For Poland, the estimated β coefficients are displayed in Figure 4.1. The upper graph is the estimate for the institutionally traded sample including 20 stocks, the lower graph for the institutional sample with 28 stocks. All data points left of the first vertical marker contain January data from only the pre-event period, all points right of the second vertical marker only include January stock returns from the post-event period. The coefficients in between the two vertical lines were obtained from samples covering January stock returns from both the post- and the pre-event periods.

[Insert Figure 4.1 here]

In consistence with our theoretical proposition, we observe a drastic decline of the β parameter over time. For the pre-event period, β estimates are large. The inclusion of post-event data leads to a decrease in the estimated β coefficients. Once there are only data from post-event January stock returns included in the sample (the data to the right of the second vertical marker), β estimates sharply decline and stabilize on a considerably lower level. Thus, we observe a decreasing January effect exactly at the time when Polish pension fund managers entered the market.[21]

[21] These results are robust to the length of the estimation window and the size of the shift. We used estimation windows of 18, 24, and 30 months and obtained comparable results. Similarly, when moving forward the window by one week instead of one month, the results are almost identical.

Figure 4.2 shows the estimated β coefficients for the two Hungarian institutional subsamples. The βs are calculated in the same manner as for Poland. During the period before the first marker, the estimated β coefficients are about 0.50. They decline drastically to values around 0.10 after the first January stock returns from the post-event periods are included in the regressions. After the second vertical marker, the estimated β parameters increase slightly and then fall to zero. Given the fact that, contrary to the Polish market, we do not have a certain well-known starting point for institutional trading on the Hungarian stock market, the evidence is naturally not as clear-cut as the evidence for the Polish market. The tendency of falling β coefficients, however, is nevertheless strong.

[Insert Figure 4.2 here]

4.1.7 Summary and Conclusions

The increase in the number of institutional investors trading on stock markets worldwide since the end of the 1980s has been associated with a rising interest from part of financial economists in institutions' impact on stock prices. One branch of literature investigates the effect of an increase in institutional ownership on the magnitude of stock market anomalies. This study adds to the evidence available on the Monday effect (Kamara (1997), Chan, Leung, and Wang (2004)) and the size effect (Gompers and Metrick (2001)) by providing empirical results on the impact of institutional trading on the January effect.

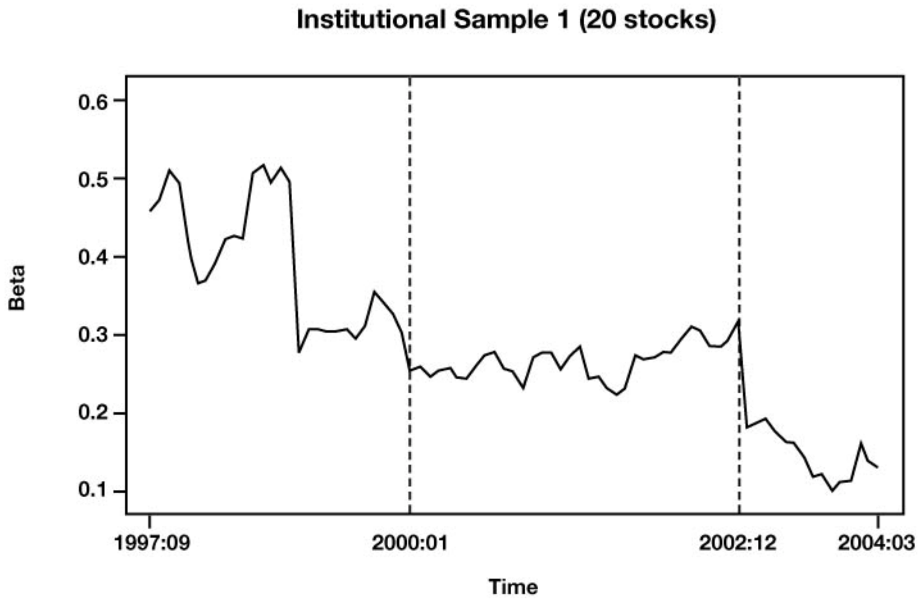
Our results shed light on the causes for the anomaly and enhance the understanding of the relationship between asset prices and the investor structure of stock markets. The major difference between previous studies and ours is the unique institutional framework we exploit to investigate the role of institutional investors for the January anomaly. After the pension system reforms in Poland on May 19, 1999, and in Hungary in 1998, pension fund investors became traders on the stock market. In contrast, before these dates the majority of traders were small, private investors. Moreover, capital gains taxes did not exist in Poland and Hungary during the period of predominantly individual trading.

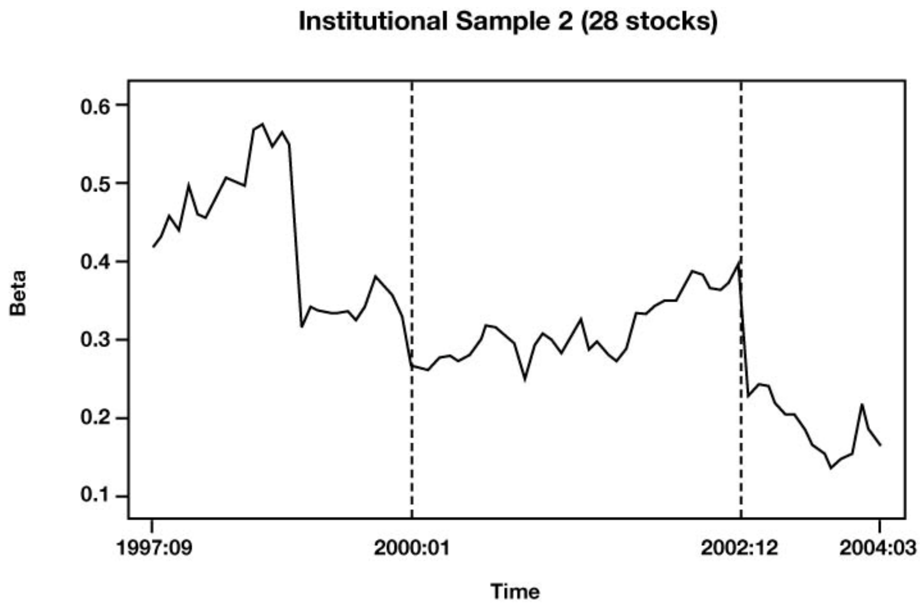
The institutional features of the Polish and the Hungarian stock markets enable us to investigate the role of individual and institutional investors on the magnitude of the January effect. Our empirical findings are twofold. First, we can empirically confirm that there is a significant January effect in Polish and Hungarian stock returns driven by the trading behavior of individuals. Due to the lack of capital gains taxes we cannot rely on the tax-loss-selling hypothesis as a rational explanation for the January effect. Instead, our findings suggest that higher stock returns in January during the period before the pension system reforms in both countries are the result of possibly sentiment-driven investment decisions by individual investors.

Second and more importantly, our empirical results show that the increase in institutional trading on the Polish and the Hungarian stock markets had a significant dampening effect on the magnitude of the January anomaly. Our evidence is comparable to the results found in Kamara (1997) and Chan, Leung, and Wang (2004) for the Monday effect as well as Gompers and Metrick (2001) for the size effect in the U.S. The window-dressing hypothesis is not supported. The empirical evidence indicates that trading by Polish and Hungarian pension funds to a certain extent arbitrages away seasonal patterns in stock returns and, therefore, increases the efficiency of both stock markets. The price effect of irrational trading patterns seems to be partly eliminated by rational investors.

4.1.8 Figures and Tables

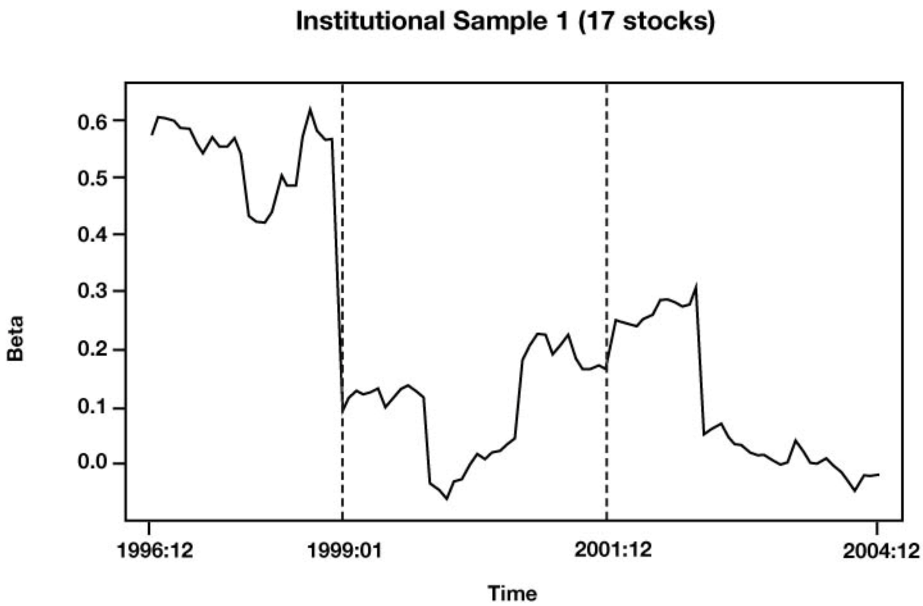
Figure 4.1: Rolling Estimation Results for Poland

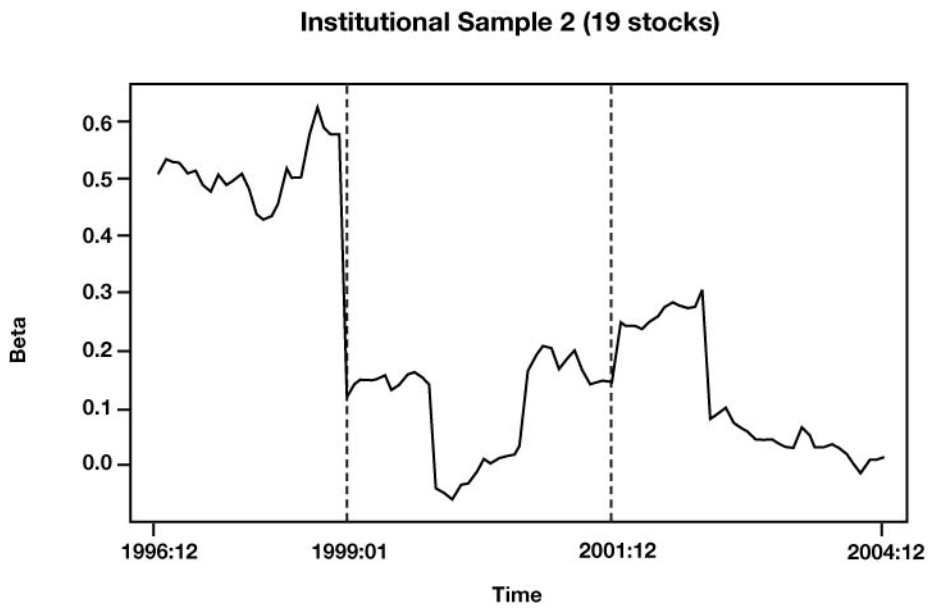




Note: Regression results of Equation (4.4) for 20 (upper graph) and 28 (lower graph) stocks actively traded by institutional investors. The figures display the evolution of the β coefficient over time. The area left of the first vertical marker corresponds to the pre-event period, and right of the second vertical marker is the post-event period.

Figure 4.2: Rolling Estimation Results for Hungary





Note: Regression results of Equation (4.4) for 17 (upper graph) and 19 (lower graph) stocks actively traded by institutional investors. The figures display the evolution of the β coefficient over time. The area left of the first vertical marker corresponds to the pre-event period, and right of the second vertical marker is the post-event period.

Table 4.1: Stocks Actively Traded by Institutional Investors

Poland		**Hungary**	
Company	Sector	Company	Sector
Panel A: Institutionally Traded Stocks (Strict Definition)			
Agora	Media	Antenna	Broadcasting
BPH	Banking	Borsodchem	Chemicals
BRE	Banking	Danubius	Hotels
BSK	Banking	Demasz	Electricity Supply
Budimex	Construction	Egis	Pharmaceuticals
Computerland	IT	Fotex	Retail Trade
Dębica	Chemicals	Magyar Telekom	Telecommunications
Echo	Construction	MOL	Oil/Natural Gas
Kęty	Metals	NABI	Engineering/Machinery
KGHM	Metals	OTP	Banking
Orbis	Hotels	Pannonplast	Plastics Industry
PBK	Banking	Pick Szeged	Food Products
Pekao	Banking	Rába	Machinery
PGF	Wholesale & Retails	Richter	Pharmaceuticals
PKN	Chemicals	Synergon	IT
Prokom	IT	TVK	Chemicals
Stomil	Chemicals	Zalakerámia	Construction
Świecie	Wood & Paper		
TPSA	Telecommunications		
WBK	Banking		
Panel B: Additional Institutionally Traded Stocks (Less Strict Definition)			
BIG	Banking	Graboplast	Textile
ComArch	IT	Prímagáz	Gas services
Elektrim	Telecommunications		
Kredyt Bank	Banking		
Netia	Telecommunications		
Optimus	IT		
Softbank	IT		
Żywiec	Food		

Note: The table presents the stocks identified as actively traded by institutional investors and the corresponding sectors. The selection criteria are described in the text. When applying the stricter (less strict) definition, 20 (28) Polish and 17 (19) Hungarian companies are included in the subsamples of institutionally traded stocks.

Table 4.2: Average Daily Stock Returns

Poland			**Hungary**		
Sample Period	January	February – December	Sample Period	January	February – December
Panel A1: Institutional Sample I ($N = 20$)			Panel A2: Institutional Sample I ($N = 17$)		
1994 – 1999	0.3964	0.0624	1994 – 1998	0.4471	0.0368
2000 – 2004	0.1618	0.0186	1999 – 2004	0.0849	−0.0166
1994 – 2004	0.2452	0.0382	1994 – 2004	0.1993	0.0010
Panel B1: Institutional Sample II ($N = 28$)			Panel B2: Institutional Sample II ($N = 19$)		
1994 – 1999	0.3902	0.0642	1994 – 1998	0.4523	0.0369
2000 – 2004	0.1758	−0.0331	1999 – 2004	0.0662	−0.0176
1994 – 2004	0.2546	0.0110	1994 – 2004	0.1973	0.0018
Panel C1: Control Sample ($N = 250$)			Panel C2: Control Sample ($N = 65$)		
1994 – 1999	0.0004	−0.0582	1994 – 1998	0.1841	−0.0556
2000 – 2004	0.0190	−0.0361	1999 – 2004	0.1134	0.0568
1994 – 2004	0.0131	−0.0452	1994 – 2004	0.1410	0.0115
Panel D1: Whole Sample ($N = 278$)			Panel D2: Whole Sample ($N = 84$)		
1994 – 1999	0.0586	−0.0406	1994 – 1998	0.2611	−0.0287
2000 – 2004	0.0385	−0.0357	1999 – 2004	0.0976	0.0319
1994 – 2004	0.0450	−0.0378	1994 – 2004	0.1588	0.0084

Note: Mean stock returns are calculated as simple arithmetic averages of daily stock returns and reported in percentage points. The overall sample period is from October 3, 1994 to March 31, 2004, for Poland and from January 3, 1994 to December 31, 2004, for Hungary. The years 1999 and 1998 mark the dates of the Polish and the Hungarian pension system reforms, respectively. N denotes the number of stocks.

Table 4.3: Empirical Results for Poland

	Regression Coefficients				
Model	$Const$	JAN_t	JAN_t^{Post}	$r_{i,t-1}$	
Panel A: Institutional Sample I ($N = 20$)					
(4.1)	0.0399***	0.3512***	−0.2306**	0.0148***	
	(0.0151)	(0.0829)	(0.1015)	(0.0053)	
(4.1)	0.0382**	0.3582***	−0.2347**		
	(0.0152)	(0.0830)	(0.1017)		
Panel B: Institutional Sample II ($N = 28$)					
(4.1)	0.0114	0.3730***	−0.2089**	0.0225***	
	(0.0133)	(0.0714)	(0.0882)	(0.0044)	
(4.1)	0.0104	0.3787***	−0.2134**		
	(0.0144)	(0.0717)	(0.0886)		
Panel C: Control Sample ($N = 250$)					
(4.1)	−0.0535***	0.0559*	0.0065	−0.0336***	
	(0.0059)	(0.0341)	(0.0408)	(0.0017)	
(4.1)	−0.0452***	0.0456†	0.0186		
	(0.0060)	(0.0344)	(0.0411)		
Panel D: Whole Sample ($N = 278$)					
(4.1)	−0.0445***	0.1069***	−0.0317	−0.0277***	
	(0.0055)	(0.0310)	(0.0372)	(0.0016)	
(4.1)	−0.0378***	0.0963***	−0.0200		
	(0.0055)	(0.0313)	(0.0375)		
Model	$Const$	$(JAN_t \times INST_i)$	$(JAN_t^{Post} \times INST_i)$	$INST_i$	$POST_t$
(4.2a)	−0.0700***	0.3872***	−0.2796**	0.0791***	0.0450***
	(0.0094)	(0.0991)	(0.1215)	(0.0189)	(0.0112)
(4.2b)	−0.0718***	0.4086***	−0.2608**	0.0534***	0.0464***
	(0.0095)	(0.0814)	(0.1008)	(0.0161)	(0.0113)

Note: The estimated models are (4.1) $r_{i,t} = \beta_0 + \beta_1 JAN_t + \beta_2 JAN_t^{Post} + \beta_3 r_{i,t-1} + u_i + e_{i,t}$ and (4.2) $r_{i,t} = \beta_0 + \beta_1(JAN_t \times INST_i) + \beta_2(JAN_t^{Post} \times INST_i) + \beta_3 INST_i + \beta_4 POST_t + u_i + e_{i,t}$, where stock returns are calculated as $r_{i,t} = 100 \ln(P_{i,t}/P_{i,t-1})$. JAN_t (JAN_t^{Post}) denotes a dummy variable which takes on the value of 1 in January throughout the whole sample period (only in the post-pension system reform period) and 0 otherwise. $INST_i$ is a dummy variable indicating a stock's affiliation to the stricter [less strict] subsample of institutionally traded shares for Equation (4.2a) [(4.2b)] with a value of 1 (0 otherwise). $POST_t$ is a dummy with value 1 for the period of increased institutional trading and 0 otherwise. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, and † at the 19% level.

Table 4.4: Empirical Results for Hungary

	Regression Coefficients				
Model	$Const$	JAN_t	JAN_t^{Post}	$r_{i,t-1}$	
Panel A: Institutional Sample I ($N = 17$)					
(4.1)	0.0003	0.4357***	−0.3541***	0.0331***	
	(0.0138)	(0.0832)	(0.0991)	(0.0051)	
(4.1)	−0.0021	0.4405***	−0.3544***		
	(0.0201)	(0.0837)	(0.0998)		
Panel B: Institutional Sample II ($N = 19$)					
(4.1)	0.0012	0.4449***	−0.3822***	0.0309***	
	(0.0132)	(0.0770)	(0.0932)	(0.0048)	
(4.1)	−0.0006	0.4468***	−0.3807***		
	(0.0181)	(0.0774)	(0.0939)		
Panel C: Control Sample ($N = 65$)					
(4.1)	0.0094	0.1701***	−0.0575	−0.0500***	
	(0.0111)	(0.0605)	(0.0760)	(0.0033)	
(4.1)	0.0115	0.1726***	−0.0707		
	(0.0112)	(0.0608)	(0.0765)		
Panel D: Whole Sample ($N = 84$)					
(4.1)	0.0067	0.2555***	−0.1598***	−0.0309***	
	(0.0087)	(0.0481)	(0.0598)	(0.0027)	
(4.1)	0.0062	0.2518***	−0.1622***		
	(0.0098)	(0.0484)	(0.0603)		
Model	$Const$	$(JAN_t \times INST_i)$	$(JAN_t^{Post} \times INST_i)$	$INST_i$	$POST_t$
(4.2a)	−0.0139	0.4801***	−0.4135***	−0.0246	0.0563***
	(0.0155)	(0.0994)	(0.1190)	(0.0223)	(0.0179)
(4.2b)	−0.0156	0.4849***	−0.4397***	−0.0218	0.0581***
	(0.0158)	(0.0909)	(0.1108)	(0.0216)	(0.0179)

Note: The estimated models are (4.1) $r_{i,t} = \beta_0 + \beta_1 JAN_t + \beta_2 JAN_t^{Post} + \beta_3 r_{i,t-1} + u_i + e_{i,t}$ and (4.2) $r_{i,t} = \beta_0 + \beta_1(JAN_t \times INST_i) + \beta_2(JAN_t^{Post} \times INST_i) + \beta_3 INST_i + \beta_4 POST_t + u_i + e_{i,t}$, where stock returns are calculated as $r_{i,t} = 100 \ln(P_{i,t}/P_{i,t-1})$. JAN_t (JAN_t^{Post}) denotes a dummy variable which takes on the value of 1 in January throughout the whole sample period (only in the post-pension system reform period) and 0 otherwise. $INST_i$ is a dummy variable indicating a stock's affiliation to the stricter [less strict] subsample of institutionally traded shares for Equation (4.2a) [(4.2b)] with a value of 1 (0 otherwise). $POST_t$ is a dummy with value 1 during the period of increased institutional trading and 0 otherwise. *** denotes statistical significance at the 1% level.

Table 4.5: Robustness Check

	Explanatory Variables					
Const	JAN_t	JAN_t^{Post}	$r_{i,t-1}$	r_{t-1}^{US}	$TIME_t$	VOL_t
Panel A: Poland – Institutional Sample I ($N = 20$)						
0.0299**	0.3404***	−0.1562†	−0.0066	0.3471***		
(0.0152)	(0.0833)	(0.1023)	(0.0053)	(0.0118)		
0.0608	0.3411***	−0.2140**	0.0148***		0.0000	
(0.0376)	(0.0845)	(0.1051)	(0.0053)		(0.0000)	
−0.4639***	0.4024***	−0.3420***	0.0143***			0.0634***
(0.1031)	(0.0835)	(0.1039)	(0.0053)			(0.0128)
0.0265	0.3420***	−0.1589†	−0.0066	0.3471***	0.0000	
(0.0376)	(0.0850)	(0.1059)	(0.0053)	(0.0118)	(0.0000)	
−0.4752***	0.3925***	−0.2687***	−0.0072	0.3472***		0.0636***
(0.1035)	(0.0839)	(0.1048)	(0.0053)	(0.0118)		(0.0129)
Panel B: Hungary – Institutional Sample I ($N = 17$)						
−0.0084	0.4344***	−0.2880***	0.0179***	0.3405***		
(0.0139)	(0.0850)	(0.1018)	(0.0052)	(0.0115)		
0.0662**	0.3969***	−0.3024***	0.0329***		0.0000**	
(0.0334)	(0.0851)	(0.1019)	(0.0051)		(0.0000)	
−0.2838***	0.5334***	−0.4594***	0.0335***			0.0403***
(0.0760)	(0.0921)	(0.1088)	(0.0053)			(0.0106)
0.0302	0.4115***	−0.2577**	0.0179***	0.3403***	0.0000	
(0.0337)	(0.0870)	(0.1047)	(0.0052)	(0.0115)	(0.0000)	
−0.2454***	0.5021***	−0.3613***	0.0182***	0.3487***		0.0336***
(0.0769)	(0.0920)	(0.1097)	(0.0054)	(0.0118)		(0.0107)

Note: The estimated equations are variants with different regressors of the model (4.3) $r_{i,t} = \beta_0 + \beta_1 JAN_t + \beta_2 JAN_t^{Post} + \beta_3 r_{i,t-1} + \mathbf{c}'\mathbf{X}_t + u_i + e_{i,t}$, where stock returns are calculated as $r_{i,t} = 100 \ln(P_{i,t}/P_{i,t-1})$. JAN_t (JAN_t^{Post}) denotes a dummy variable which takes on the value of 1 in January throughout the whole sample period (in the post-pension system reform period) and 0 otherwise. $\mathbf{X}_t' = (r_{t-1}^{US}, TIME_t, VOL_t)$ describes a set of control variables, where r_{t-1}^{US} denotes the one-period lagged return of the S&P 500 Index, $TIME_t$ a linear time trend, and VOL_t the log of aggregate trading volume in the respective home market on day t, $VOL_t = \ln(\sum_{i=1}^{n} VOL_{i,t})$, with n the number of individual stocks. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively, and † at the 14% level.

4.2 Payment Schemes, Individual Traders' Investment Decisions, and Stock Market Anomalies

4.2.1 Motivation and Literature Review

Calendar anomalies have played an important role in the finance literature challenging the efficient market hypothesis (Fama (1970)). While voluminous international evidence and a number of explanations are available, so far researchers have had limited success in identifying underlying causes which generate stock market anomalies. In this section, we provide deeper insight into this issue highlighting the role of payments individual investors receive on a monthly basis. First, salary payments at the end or the beginning of each month enable individual investors to invest part of their income in the stock market. The concentration of flow of funds to investors may be responsible for an anomalous pattern in stock returns in the turn-of-the-month trading days in case fundamentally relevant information is not available at that time. Second, if individual investors postpone their investment decision to the weekend due to time considerations, the availability of financial resources at the end or the beginning of the month may induce abnormally high stock returns on the first Mondays of each month.

The first argument mentioned above has its origin in the literature on the turn-of-the-month effect. Ariel (1987) shows for U.S. data that virtually all of the cumulative stock return appears on the last day of the month and the consecutive first nine trading days of the following month. Lakonishok and Smidt (1988) confirm this finding for U.S. stock returns over a period of 90 years of daily data for the last and the first three days of the month, while Cadsby and Ratner (1992) provide mixed empirical evidence using an international data set. Ogden (1990) provides an explanation for the turn-of-the-month effect relying on the standardization of payments at the turn of each calendar month for the U.S.

While the turn-of-the-month effect does not discriminate between weekdays, the Monday effect takes into account that stock returns are different on Mondays relative to the rest of trading days of the week. According to this calendar anomaly, mean stock returns are significantly negative on Mondays and lower than on other weekdays. The Monday effect is well-documented for the U.S. (French (1980)) and other mature stock markets (Jaffe, Westerfield, and Ma (1989)).[22] One of the possible explanations for the Monday anomaly is the specific trading behavior of individual investors. Following

[22] For a comprehensive survey of the Monday effect literature see Pettengill (2003).

Miller (1988), Ritter (1988), and Lakonishok and Maberly (1990), individual investors typically do not have time during the weekday trading hours and, therefore, process information and undertake investment decisions only during the weekend. In addition, Lakonishok and Maberly (1990) find that, when the stock market re-opens on Monday, individual investors tend to increase selling activity relative to the rest of the week. The relative higher selling activities by individuals on Mondays compared to the rest of the week explains, at least in part, the weekend anomaly.

More recently, Brusa, Liu, and Schulman (2003), Brusa and Liu (2004), and Gu (2004) provide evidence in favor of a reversed Monday effect since 1988 for the U.S., i.e., Monday stock returns are on average significantly positive and higher than on other days of the week. Moreover, positive Monday stock returns are concentrated in the first and third weeks of the month. While the explanation for the traditional Monday effect outlined above relies on the trading pattern of individual investors, the increased trading activities of institutional investors provide an explanation for the reversed Monday effect. Since the Monday anomaly has become a well-known pattern in stock returns, sophisticated investors may now fully or over-exploit the opportunity for abnormal stock returns. Consequently, institutional investors eliminate or reverse the Monday anomaly found in pre-1988 samples.

We provide new evidence on the turn-of-the-month and the Monday effect relying on daily time series of individual Polish and Hungarian stocks. Both emerging stock markets exhibit a specific institutional setting in terms of the investor structure, which allows a meaningful contribution to the literature on stock market calendar anomalies. Before the pension system reforms in Poland and Hungary, predominantly individual investors populated both stock markets. Given the concentration of cash flows to private investors at the turn of the month, we expect a surge in stock returns on the trading days around the turn of the month and the first Mondays of the month. The sudden appearance of institutional traders due to the pension system reforms may induce a structural change. The dominance of individual investors during the pre-pension system reform period and the increased institutional ownership afterwards provide a unique institutional environment to investigate the role of individual investors' trading decisions. Additionally, the significance of increased institutional ownership on asset price dynamics can be assessed.

The remainder of the section proceeds as follows. Subsection 4.2.2 outlines the institutional background for Poland and Hungary. The econometric methodology is described in Subsection 4.2.3, while Subsection 4.2.4 characterizes the data set. Subsection 4.2.5 contains the empirical findings, and Subsection 4.2.6 summarizes and concludes.

4.2.2 Institutional Background

4.2.2.1 Poland

Re-established in 1991, the Polish stock market has grown rapidly during the last decade in terms of both the number of companies listed and market capitalization. In comparison to the two other European Union accession countries in the region, the Czech Republic and Hungary, the capitalization of the Polish stock market is significantly higher. It is comparable to that of the smaller mature European stock markets like Austria and was about 60 billion US$ at the end of 2004 (WSE (2005)).

Before the pension system reform in Poland in 1999, predominantly individual traders invested on the stock market. In 1999, the public pension system was enriched by a private component, represented by open-end pension funds. Participation in this component is mandatory for employees below certain age. They are obliged to transfer 7.3% of their gross salary to the government-run social insurance institute called Zakład Ubezpieczeń Społecznych (ZUS), which in turn transfers the collected contributions to the pension funds.[23]

The first transfer of money from the ZUS to the pension funds took place on May 19, 1999. This date marks a change of the investor structure on the Polish stock market. Before 1999, about 20% *domestic institutional* investors and 45% *domestic individual* investors traded at the Warsaw Stock Exchange. Over time the proportion of domestic institutional traders has increased, whereas the relative importance of individual investors has decreased. In 2004, approximately one-third of the investors were domestic individuals, and about one-third were national institutions. Constantly about one-third of the investors on the Polish stock market adhere to the group of *foreign* investors.

4.2.2.2 Hungary

The Budapest Stock Exchange, re-established in 1990, experienced a significant increase in its capitalization, attaining about 6 billion US$ in 1996, mainly due to the

[23] For a more detailed description of the Polish pension system and for further references see Voronkova and Bohl (2005).

privatization of Hungary's bigger state-owned companies such as Mol, OTP, Gedeon Richter, and Matav. In the following years, the stock market went through a phase of continuous growth, reaching a capitalization of 30 billion US$ at the end of 2004. Similarly, in Hungary private pension funds were founded in 1997 and started their financial activities in 1998. Before 1998, primarily small individual investors populated the Hungarian stock market.

In both countries the payment of salaries is concentrated around the turn of the month. Although differences do exist between some pensioners and employed people, in the majority of cases salary payment is transferred to the account before the tenth of the following month. The Polish and Hungarian labor codes define officially the tenth of each month as the latest date of salary payment. Nevertheless, surveying people employed in Poland or Hungary indicates that salary is available earlier. In consequence, a concentration of flow of funds to potential stock market investors is given in both countries.

4.2.3 Methodology

We assess the effect of increased institutional trading on the magnitude of two stock market seasonalities.[24] In the empirical investigation we rely on a panel framework and investigate separately two data sets of Polish and Hungarian stocks. The look beyond aggregate index data proves beneficial since we can exploit the richer information in the cross-section of returns. Moreover, the advantages of a panel data model over a purely time-series investigation of index data or individual shares are manifold (see, e.g., Baltagi (2005)). Most importantly, unobserved individual heterogeneity can be controlled for that would otherwise have to go undetected and could generate biased results. For the turn-of-the-month and the Monday effect the following one-way error component regression models are run, respectively:

$$r_{i,t} = \alpha_0 + \alpha_1 TOM_t + \alpha_2 TOM_t^{Inst} + \alpha_3 r_{t-1}^{US} + \alpha_4 r_{i,t-1} + u_i + e_{i,t}, \tag{4.5}$$

$$r_{i,t} = \beta_0 + \beta_1 FirstMon_t + \beta_2 FirstMon_t^{Inst} + \beta_3 r_{t-1}^{US} + \beta_4 r_{i,t-1} + v_i + \nu_{i,t}. \tag{4.6}$$

The subscript i denotes the cross-sectional and t the time-series dimension of the data set. The dependent variable is the daily stock return $r_{i,t}$, calculated as the logarithmic

[24] The Polish pension system reform, the associated increase in institutional trading, and its implications for market efficiency/stabilization have been investigated with different foci in previous literature: Bohl, Brzeszczyński, and Wilfling (2008) and Bohl and Brzeszczyński (2006) examine stock return volatility, Gębka, Henke, and Bohl (2006) return autocorrelation, and Voronkova and Bohl (2005) scrutinize the investment behavior of pension funds.

difference in prices $r_{i,t} = 100 \ln(P_{i,t}/P_{i,t-1})$. $P_{i,t}$ denotes the individual stock price at the close of every trading day.

The dummy variables in Equations (4.5) and (4.6) are defined as follows. TOM_t is a turn-of-month dummy variable which takes on the value of 1 for the last and the first *five* trading days of each month throughout the whole sample period (0 otherwise). In an alternative specification, TOM_t is 1 for the last and the first *three* trading days of each month (0 otherwise). The dummy variable TOM_t^{Inst} is 1 only for those turn-of-month trading days that fall into the period of increased institutional trading at the Warsaw and Budapest Stock Exchanges, i.e., beginning with June 1999 for Poland and January 1999 for Hungary (0 otherwise). Accordingly, $FirstMon_t$ is a Monday indicator variable which is 1 for the first Monday and, alternatively, for the first and second Mondays of each month (0 otherwise). $FirstMon_t^{Inst}$ captures the first Monday(s) of each month during the period of increased institutional trading with a value of 1 and is 0 otherwise.

In addition, lagged U.S. stock index returns r_{t-1}^{US} are included in both regressions to take into account the international influence on both emerging stock markets. We also allow for stock returns autocorrelation in the time-series dimension by including the lagged dependent variable $r_{i,t-1}$ as an additional explanatory variable.[25] u_i and υ_i denote unobservable stock-specific random effects: $u_i \sim N(0, \sigma_u^2)$ and $\upsilon_i \sim N(0, \sigma_\upsilon^2)$. $e_{i,t}$ and $\nu_{i,t}$ are the remainder disturbances: $e_{i,t} \sim N(0, \sigma_e^2)$ and $\nu_{i,t} \sim N(0, \sigma_\nu^2)$.[26]

In the above specifications, a positive and significant parameter α_1 (β_1) provides evidence in favor of a turn-of-the-month (Monday) effect in stock returns. For the interpretation of the parameters α_2 and β_2, three cases have to be distinguished. First, a negative and significant coefficient α_2 (β_2) indicates a reduction of positive turn-of-the-month (Monday) stock returns due to the entrance of pension funds as institutional investors into the market. Second, if α_2 (β_2) is positive and significant, then institutional investors' trading behavior strengthens the effects. Third, if α_2 (β_2) is statistically insignificant, institutions do not have an influence on the effects. The sum $\alpha_1 + \alpha_2$ ($\beta_1 + \beta_2$) provides a measure of the magnitude of the turn-of-the-month (Monday) effect in the period of increased institutional trading.

[25] In panels with a short time dimension the presence of lagged dependent variables causes inconsistent and biased estimates. However, in our case T is quite large so that the bias resulting from the presence of a lagged dependent variable can be neglected (Judson and Owen (1999), Baltagi (2005)).

[26] The model selection is supported by Hausman specification tests (Hausman (1978)). We also test for serial correlation in the error distribution with Lagrange-multiplier (LM) tests (Breusch (1978), Godfrey (1978)).

4.2.4 Data

4.2.4.1 Data Sources

Poland. The data for Poland contain daily closing prices for all stocks listed on the Warsaw Stock Exchange in the period from October 3, 1994 to March 31, 2004.[27] These time series were directly provided by the Warsaw Stock Exchange (WSE). Altogether, the sample comprises 278 firms over the indicated sample period. The time series are stock-split adjusted.

To investigate the impact of the pension funds' investment activities, we construct a subsample of actively institutionally traded stocks as follows. We calculate a measure of each stock's institutional coverage by dividing the aggregate pension fund holdings of that stock by the overall aggregate pension fund holdings in a particular year. This measure can be interpreted as the percentage share of a particular stock in the aggregate pension fund holdings. A stock is defined as actively institutionally traded in a given year if the measure of relative institutional holdings exceeds 1%.[28]

We calculate this measure for all stocks and all years separately during the 1999–2003 period and end up with five yearly measures of relative pension fund holdings for each individual stock. A stock is included in the sample of actively institutionally traded stocks if the pension fund holding measure of this stock exceeds the 1% level in at least two out of the five years, equivalent to 40% of the post-event period. This criterion results in the identification of 28 stocks as institutionally traded. Columns 1 and 2 of Table 4.6 provide additional information about these stocks. Whereas Polish pension fund investors do not have a preference for stocks of a specific sector, they concentrate their investments on large firms' stocks.

[Insert Table 4.6 here]

[27] The selection of the start date is due to the following reasoning. Shortly after its re-opening, the Polish stock market experienced a stock price increase of 924% from May 6, 1993 to March 8, 1994, and a subsequent crash. Furthermore, it was not until October 3, 1994, that trading on the Warsaw Stock Exchange was extended from four days to five days a week. Starting our inquiry at the beginning of October 1994 ensures that the empirical findings are neither distorted by the bubble and crash periods nor affected by the change in trading frequency.

[28] We drop stocks with only marginal institutional coverage as for these stocks institutional trading behavior may not have a large impact on stock returns. The 1% cut-off point is arbitrarily chosen but proved to be an acceptable compromise for the purpose of our study: On the one hand, it allows us to eliminate those stocks which are not at all or only marginally covered by institutional investors and to come up with a limited number of stocks that are actively traded by institutions. On the other hand, the size of the resulting subsamples is still sufficient for econometric testing.

Hungary. For Hungary, the data consist of daily closing prices for the stocks listed on the Budapest Stock Exchange in the period from January 3, 1994 to December 31, 2004. The time series were obtained from Thomson Financial Datastream. Altogether, the cross-section of the sample comprises 84 firms.[29]

To determine a subsample of institutionally traded stocks for the Hungarian stock market, we requested the portfolio holdings of all Hungarian pension funds. The pension funds' replies show that their stock market investment decisions closely mirror the composition of the main stock index BUX. In the sample of Hungarian stocks actively traded by institutional investors, we therefore focus on the stocks included in the BUX. Information on the BUX composition was provided by the Budapest Stock Exchange (BSE) for the 1996–2004 period. Contrary to Poland, we do not use a 1% cut-off criterion because the BUX is dominated by very few stocks with high weights. Hence, a cut-off point as the one mentioned above would considerably reduce our sample in size. The number of stocks included in the institutional sample would be too small to conduct a cross-sectional investigation.

As a definition of institutionally traded stocks that is roughly in line with the selection criterion for Poland, we use all stocks that are included in the BUX for at least 40% of the time in the post-reform sample period from 1998 to 2004. This definition results in the identification of 19 institutionally traded stocks. Columns 3 and 4 of Table 4.6 list the Hungarian companies selected together with their sector affiliations.

4.2.4.2 Summary Statistics

Table 4.7 and 4.8 report some descriptive statistics for the data set: Table 4.7 shows average stock returns on turn-of-the-month versus regular trading days, and Table 4.8 displays average Monday returns as compared to the rest of the week. Both tables contain daily mean returns for the actively institutionally traded and the non-institutionally traded stocks as well as the complete sample of stocks. These are calculated for the entire period as well as pre- and post-reform periods for Poland (Panel A) and Hungary (Panel B). In addition, the number of observations is reported.

[29] Since we lack information on stock splits for Hungary, a conservative estimation approach is called for in order to mitigate the impact of potential outliers (due to stock splits or other factors). Therefore we applied a trimming procedure to the data set, deleted the 0.5% of highest and lowest returns, and generated all results for the modified data set. Since the influence of outliers seems to be marginal, we rely on this setting as a robustness check and do not report results in the following. The same robustness check was carried out for Poland.

As can be seen from Table 4.7, average stock returns for turn-of-the-month trading days are positive and higher compared to the mean return for the remaining trading days of the month, with the average turn-of-month return amounting to up to 25 basis points over the entire investigation period for the Polish institutional sample. Moreover, mean stock returns are higher during the pre- than during the post-reform period. For Poland, pre-reform turn-of-month returns are about five times higher than their post-reform counterparts throughout all samples and drop from 49 to 11 basis points for the subsample of institutionally traded stocks. For Hungary, the observed difference is less pronounced.

Table 4.8 contains mean Monday stock returns as they are distributed across the month, i.e., all Mondays in a given month are numbered from 1 to 4 or 5.[30] While the first Monday of each month exhibits on average a positive stock return, the following Mondays show returns which are much lower and often negative. Similar to the picture conveyed in Table 4.7, mean stock returns are substantially lower in the post- compared to the pre-reform period. This pattern is very clear-cut for all Polish subsamples. For instance, average returns on the first Monday of the month are about 64 basis points among institutionally covered stocks over the entire sample period, a sharp decline from 106 to 39 basis points being detected from pre- to post-reform period. For Hungary, both absolute numbers for the Monday effect and the drop from pre- to post-reform returns are considerably higher for the institutional subsample.

[Insert Table 4.7 here]

[Insert Table 4.8 here]

4.2.5 Empirical Results

Table 4.9 displays the empirical findings from regression model (4.5) for the turn-of-the-month effect. We find evidence in favor of a pronounced turn-of-the-month effect in the period when the Polish and the Hungarian stock markets were dominated by individual investors. This holds for all subsamples with the exception of the non-institutional sample for Hungary, where there seem to be no increased returns around the turn of the month. Nearly all other coefficient estimates of the dummy variable

[30] This approach slightly differs from Brusa and Liu (2004), where the authors use the belonging of each Monday to a particular week of the month as an ordering scheme. For the purpose of our inquiry, however, the classification outlined above is more straightforward and appealing.

TOM_t are statistically significant at the 1% level, ranging in absolute height from 0.55 (institutional sample Poland) to 0.13 (whole sample Hungary).

Moreover, for all Polish samples the magnitude of the turn-of-the-month effect decreases notably in the period after the pension fund investors' entrance into the stock market, measured by the coefficients of the institutional investor dummy TOM_t^{Inst}. The estimated parameter values are all highly significant and lie between -0.39 and -0.17. The anomalous turn-of-the-month effect in stock returns does not entirely disappear after the entrance of pension funds as institutional investors into the Polish stock market. However, its magnitude becomes substantially lower. The Hungarian stock market experiences this development to a lesser extent, and only in the subsample of the 19 stocks most covered by institutional investors we do perceive a significant decline in previously above-average turn-of-month returns.[31]

[Insert Table 4.9 here]

The empirical results for the Monday effect as estimated in Equation (4.6) are displayed in Table 4.10. The estimation results for both countries show clearly superior returns on the first Monday of the month in the period before the increased investment activities of pension funds started. The estimated parameters of the dummy variable $FirstMon_t$ are between 1.06 and 0.92 for Poland (all statistically significant at 1% level) and between 0.64 and 0.21 for Hungary (all statistically significant at 10% level or better).[32]

The anomalous returns on the first Monday of the month, again, decrease drastically after the entrance of pension funds into the Polish stock market with statistically significant coefficients for $FirstMon_t^{Inst}$ of about -0.70. For Hungary, we can attest a significant downturn in abnormally high First-Monday returns due to intensified investment activities by institutional investors in all but the non-institutional subsamples.

[Insert Table 4.10 here]

[31] The findings for the alternative specification when turn-of-month trading days are defined as the last trading day of a given month plus the first three trading days of the following month are qualitatively the same but less pronounced (not reported but available upon request). Since the payment of salaries is somewhat scattered around the turn of the month, we are not overly surprised by this outcome.

[32] Again, findings are qualitatively identical but less marked in absolute numbers when investigating the abnormal returns on the first and second Monday of the month relative to the remaining trading days. The results of this robustness check are not reported but can be obtained from the author upon request.

All results are robust across different specifications of the regression equations and are qualitatively unaffected by the inclusion of the lagged dependent variable $r_{i,t-1}$ and lagged U.S. stock returns r^{US}_{t-1}. We find a significant positive relationship between lagged U.S. stock returns and the performance of the two emerging stock markets investigated as well as significant negative return autocorrelation for all except for the institutional subsamples.

4.2.6 Summary and Conclusions

This article examines the role of payments individual investors receive explaining the turn-of-the-month effect and the Monday effect. The empirical investigation relies on daily time series of individual Polish and Hungarian stocks which are analyzed in a panel framework. The stock markets in Poland and Hungary provide an interesting institutional framework to study both stock market anomalies: Before the pension system reforms in both countries at the end of the 1990s, primarily individual investors populated the stock markets. This provides the basis for investigating the importance of the concentration of cash flows individual investors receive at the end and the beginning of each month in explaining the turn-of-the-month and the Monday anomaly. Moreover, the increased institutional ownership due to the pension system reform provides information about a structural change and the influence of institutional investors on the anomalies.

In Poland and Hungary, salaries of employed people are normally paid at the end of each month so that a concentration of cash flows appears at the beginning of each month. During the period of primarily individual trading the evidence is favorable for a pronounced turn-of-the-month effect and anomalously high stock returns on the first Monday of each month. Hence, regular payment schemes seem to be driving forces of both stock market anomalies. After the entrance of institutional investors into both stock markets due to the pension system reform the magnitude of both anomalies decrease notably in the majority of cases analyzed. This refers in particular to the subsamples of actively institutionally traded stocks. If stock returns exhibit exploitable regularities, then smart traders are expected to take advantage of these patterns, thereby earning abnormal profits. On stock markets with a sufficiently large number of institutional investors as smart traders, anomalies are supposed to disappear as the trading of this investor group arbitrages away seasonal patterns in returns.

4.2.7 Tables

Table 4.6: Stocks Actively Traded by Institutional Investors

Poland		**Hungary**	
Company	Sector	Company	Sector
Agora	Media	Antenna	Broadcasting
BPH	Banking	Borsodchem	Chemicals
BRE	Banking	Danubius	Hotels
BSK	Banking	Demasz	Electricity Supply
Budimex	Construction	Egis	Pharmaceuticals
Computerland	IT	Fotex	Retail Trade
Dębica	Chemicals	Magyar Telekom	Telecommunications
Echo	Construction	MOL	Oil/Natural Gas
Kęty	Metals	NABI	Engineering/Machinery
KGHM	Metals	OTP	Banking
Orbis	Hotels	Pannonplast	Plastics Industry
PBK	Banking	Pick Szeged	Food Products
Pekao	Banking	Rába	Machinery
PGF	Wholesale & Retails	Richter	Pharmaceuticals
PKN	Chemicals	Synergon	IT
Prokom	IT	TVK	Chemicals
Stomil	Chemicals	Zalakerámia	Construction
Świecie	Wood & Paper		
TPSA	Telecommunications		
WBK	Banking		

Note: The table presents the stocks identified as actively traded by institutional investors and their corresponding sectors. The selection criteria are described in the text.

Table 4.7: Average Turn-of-Month Stock Returns

	Entire Period		Pre-Reform Period		Post-Reform Period	
Trading Days	Mean	Obs.	Mean	Obs.	Mean	Obs.
Panel A: Poland						
Institutional Sample (28 Stocks)						
Regular	−0.0583	36,487	−0.1027	13,318	−0.0327	23,169
Turn-of-Month	0.2495	14,743	0.4926	5,447	0.1070	9,296
Total	0.0303	51,230	0.0701	18,765	0.0073	32,465
Non-Institutional Sample (250 Stocks)						
Regular	−0.1161	242,114	−0.2216	75,689	−0.0681	166,425
Turn-of-Month	0.1068	97,579	0.2382	30,767	0.0463	66,812
Total	−0.0521	339,693	−0.0887	106,456	−0.0353	233,237
Whole Sample (278 Stocks)						
Regular	−0.1085	278,601	−0.2038	89,007	−0.0638	189,594
Turn-of-Month	0.1255	112,322	0.2765	36,214	0.0537	76,108
Total	−0.0413	390,923	−0.0649	125,221	−0.0301	265,702
Panel B: Hungary						
Institutional Sample (19 Stocks)						
Regular	−0.0372	31,183	−0.0182	11,079	−0.0476	20,104
Turn-of-Month	0.1660	11,851	0.3015	4,189	0.0920	7,662
Total	0.0188	43,034	0.0695	15,268	−0.0091	27,766
Non-Institutional Sample (65 Stocks)						
Regular	−0.0621	67,760	−0.0784	27,339	−0.0511	40,421
Turn-of-Month	−0.0002	25,766	0.0059	10,357	−0.0042	15,409
Total	−0.0450	93,526	−0.0552	37,696	−0.0381	55,830
Whole Sample (84 Stocks)						
Regular	−0.0542	98,943	−0.0610	38,418	−0.0499	60,525
Turn-of-Month	0.0522	37,617	0.0910	14,546	0.0277	23,071
Total	−0.0249	136,560	−0.0193	52,964	−0.0285	83,596

Note: Mean stock returns are calculated as simple arithmetic averages of daily returns and reported in percent. “Turn-of-Month” trading days are defined as the last trading day of a given month plus the first five trading days of the following month. All other trading days are subsumed under the label “Regular”. “Obs.” denotes the number of observations. For Poland the overall sample period is from October 3, 1994 to March 31, 2004. May 19, 1999 marks the date of the Polish pension system reform. For Hungary the overall sample period is from January 3, 1994 to December 31, 2004. January 1, 1999 approximately marks the date of the Hungarian pension system reform.

Table 4.8: Average Monday Stock Returns

	Entire Period		Pre-Reform Period		Post-Reform Period	
Position of Monday	Mean	Obs.	Mean	Obs.	Mean	Obs.
Panel A: Poland						
Institutional Sample (28 Stocks)						
1^{st} Monday in Month	0.6382	2,274	1.0635	836	0.3909	1,438
2^{nd} –"–	−0.1374	2,342	0.1218	823	−0.2778	1,519
3^{rd} –"–	−0.1450	2,395	−0.0749	904	−0.1875	1,491
4^{th} –"–	−0.1421	2,363	−0.1335	874	−0.1472	1,489
5^{th} –"–	−0.2518	843	−0.0535	283	−0.3520	560
All Mondays	0.0229	10,217	0.2123	3,720	−0.0855	6,497
Non-Institutional Sample (250 Stocks)						
1^{st} Monday in Month	0.4769	14,999	0.9768	4,672	0.2508	10,327
2^{nd} –"–	0.0238	15,607	0.3518	4,703	−0.1177	10,904
3^{rd} –"–	−0.1496	15,920	−0.0278	5,185	−0.2084	10,735
4^{th} –"–	−0.0269	15,690	−0.1203	4,992	0.0167	10,698
5^{th} –"–	−0.0770	5,611	0.0781	1,620	−0.1400	3,991
All Mondays	0.0632	67,827	0.2645	21,172	−0.0281	46,655
Whole Sample (278 Stocks)						
1^{st} Monday in Month	0.4981	17,273	0.9899	5,508	0.2679	11,765
2^{nd} –"–	0.0028	17,949	0.3175	5,526	−0.1372	12,423
3^{rd} –"–	−0.1490	18,315	−0.0348	6,089	−0.2059	12,226
4^{th} –"–	−0.0420	18,053	−0.1222	5,866	−0.0033	12,187
5^{th} –"–	−0.0998	6,454	0.0586	1,903	−0.1660	4,551
All Mondays	0.0580	78,044	0.2567	24,892	−0.0351	53,152

(Continued)

Table 4.8 – Continued

	Entire Period		Pre-Reform Period		Post-Reform Period	
Position of Monday	Mean	Obs.	Mean	Obs.	Mean	Obs.
Panel B: Hungary						
Institutional Sample (19 Stocks)						
1^{st} Monday in Month	0.3165	1,973	0.6421	696	0.1390	1,277
2^{nd} –"–	0.0821	1,978	0.2359	701	−0.0024	1,277
3^{rd} –"–	−0.0755	1,979	−0.1850	703	−0.0151	1,276
4^{th} –"–	−0.0590	1,981	−0.1706	705	0.0026	1,276
5^{th} –"–	0.1517	691	0.3360	247	0.0492	444
All Mondays	0.0727	8,602	0.1458	3,052	0.0325	5,550
Non-Institutional Sample (65 Stocks)						
1^{st} Monday in Month	0.0458	4,291	0.1607	1,723	−0.0313	2,568
2^{nd} –"–	−0.0783	4,290	0.0615	1,726	−0.1725	2,564
3^{rd} –"–	−0.1685	4,300	0.1487	1,737	−0.3834	2,563
4^{th} –"–	−0.0522	4,309	0.0204	1,742	−0.1014	2,567
5^{th} –"–	−0.0065	1,505	−0.1925	611	0.1206	894
All Mondays	−0.0588	18,695	0.0742	7,539	−0.1486	11,156
Whole Sample (84 Stocks)						
1^{st} Monday in Month	0.1311	6,264	0.2992	2,419	0.0253	3,845
2^{nd} –"–	−0.0277	6,268	0.1119	2,427	−0.1159	3,841
3^{rd} –"–	−0.1392	6,279	0.0526	2,440	−0.2610	3,839
4^{th} –"–	−0.0543	6,290	−0.0346	2,447	−0.0669	3,843
5^{th} –"–	0.0433	2,196	−0.0404	858	0.0969	1,338
All Mondays	−0.0173	27,297	0.0948	10,591	−0.0884	16,706

Note: Mean stock returns are calculated as simple arithmetic averages of daily returns and reported in percent. "Turn-of-Month" trading days are defined as the last trading day of a given month plus the first five trading days of the following month. All other trading days are subsumed under the label "Regular". "Obs." denotes the number of observations. For Poland the overall sample period is from October 3, 1994 to March 31, 2004. May 19, 1999 marks the date of the Polish pension system reform. For Hungary the overall sample period is from January 3, 1994 to December 31, 2004. January 1, 1999 approximately marks the date of the Hungarian pension system reform.

Table 4.9: Regression Results for the Turn-of-the-Month Effect

	Regression Coefficients				
	$Const$	TOM_t	TOM_t^{Inst}	r_{t-1}^{US}	$r_{i,t-1}$
Panel A: Poland					
Institutional Sample (28 Stocks)					
	-0.0571^{***}	0.4911^{***}	-0.3362^{***}	0.3774^{***}	0.0111
	(0.0166)	(0.0508)	(0.0554)	(0.0138)	(0.0081)
	-0.0583^{***}	0.5509^{***}	-0.3856^{***}		
	(0.0166)	(0.0506)	(0.0553)		
Non-Institutional Sample (250 Stocks)					
	-0.1497^{***}	0.3199^{***}	-0.1722^{***}	0.3436^{***}	-0.0323^{***}
	(0.0393)	(0.0230)	(0.0274)	(0.0063)	(0.0085)
	−0.3125	0.3528^{***}	-0.1896^{***}		
	(0.2329)	(0.0231)	(0.0273)		
Whole Sample (278 Stocks)					
	-0.1395^{***}	0.3476^{***}	-0.1997^{***}	0.3489^{***}	-0.0287^{***}
	(0.0355)	(0.0210)	(0.0249)	(0.0058)	
	−0.2851	0.3825^{***}	-0.2190^{***}		
	(0.2092)	(0.0211)	(0.0248)		
Panel B: Hungary					
Institutional Sample (19 Stocks)					
	-0.0410^{**}	0.2964^{***}	-0.1692^{***}	0.4136^{***}	−0.0057
	(0.0163)	(0.0575)	(0.0630)	(0.0175)	(0.0153)
	-0.0381^{**}	0.3376^{***}	-0.2079^{***}		
	(0.0179)	(0.0559)	(0.0613)		
Non-Institutional Sample (65 Stocks)					
	-0.0734^{***}	0.0621	−0.0027	0.1089^{***}	-0.0748^{***}
	(0.0252)	(0.0730)	(0.0856)	(0.0211)	(0.0151)
	-0.0621^{**}	0.0680	−0.0101		
	(0.0250)	(0.0711)	(0.0833)		
Whole Sample (84 Stocks)					
	-0.0637^{***}	0.1318^{**}	−0.0487	0.2149^{***}	-0.0684^{***}
	(0.0180)	(0.0547)	(0.0627)	(0.0153)	(0.0138
	-0.0542^{***}	0.1453^{***}	−0.0633		
	(0.0178)	(0.0529)	(0.0608)		

Note: The model estimated is (4.5) $r_{i,t} = \alpha_0 + \alpha_1 TOM_t + \alpha_2 TOM_t^{Inst} + \alpha_3 r_{t-1}^{US} + \alpha_4 r_{i,t-1} + u_i + e_{i,t}$, where stock returns are calculated as $r_{i,t} = 100 \ln(P_{i,t}/P_{i,t-1})$. TOM_t (TOM_t^{Inst}) denotes a dummy variable which takes on the value of 1 for the last and the first five trading days of each month throughout the whole sample period (during the period of increased institutional trading at the Warsaw and Budapest Stock Exchanges) and 0 otherwise. ** and *** denote statistical significance at the 5% and 1% level, respectively.

Table 4.10: Regression Results for the Monday Effect

	Regression Coefficients				
	$Const$	$FirstMon_t$	$FirstMon_t^{Inst}$	r_{t-1}^{US}	$r_{i,t-1}$
Panel A: Poland					
Institutional Sample (28 Stocks)					
	0.0011	0.9236***	−0.6735***	0.3770***	0.0109
	(0.0142)	(0.1360)	(0.1528)	(0.0138)	(0.0081)
	0.0021	1.0615***	−0.6727***		
	(0.0142)	(0.1311)	(0.1482)		
Non-Institutional Sample (250 Stocks)					
	−0.1126***	0.9690***	−0.7207***	0.3422***	−0.0325***
	(0.0384)	(0.0599)	(0.0724)	(0.0063)	(0.0085)
	−0.2796	1.0488***	−0.7204***		
	(0.2452)	(0.0580)	(0.0708)		
Whole Sample (278 Stocks)					
	−0.1001***	0.9659***	−0.7162***	0.3476***	−0.0289***
	(0.0347)	(0.0549)	(0.0660)	(0.0058)	(0.0079)
	−0.2495	1.0497***	−0.7134***		
	(0.2202)	(0.0531)	(0.0644)		
Panel B: Hungary					
Institutional Sample (19 Stocks)					
	0.0005	0.5596***	−0.5475***	0.4149***	−0.0053
	(0.0145)	(0.1215)	(0.1387)	(0.0175)	(0.0153)
	0.0032	0.6358***	−0.5002***		
	(0.0165)	(0.1181)	(0.1342)		
Non-Institutional Sample (65 Stocks)					
	−0.0612***	0.2180*	−0.2095	0.1092***	−0.0748***
	(0.0221)	(0.1137)	(0.1581)	(0.0211)	(0.0151)
	−0.0494**	0.2101*	−0.1920		
	(0.0219)	(0.1108)	(0.1517)		
Whole Sample (84 Stocks)					
	−0.0419***	0.3181***	−0.3070***	0.2156***	−0.0683***
	(0.0158)	(0.0886)	(0.1171)	(0.0153)	(0.0138)
	−0.0324**	0.3316***	−0.2739**		
	(0.0157)	(0.0859)	(0.1123)		

Note: The model estimated is (4.6) $r_{i,t} = \alpha_0 + \alpha_1 FirstMon_t + \alpha_2 FirstMon_t^{Inst} + \alpha_3 r_{t-1}^{US} + \alpha_4 r_{i,t-1} + \upsilon_i + \nu_{i,t}$, where stock returns are calculated as $r_{i,t} = 100\ln(P_{i,t}/P_{i,t-1})$. $FirstMon_t$ ($FirstMon_t^{Inst}$) denotes a dummy variable which takes on the value of 1 for the first Monday of each month throughout the whole sample period (during the period of increased institutional trading at the Warsaw and Budapest Stock Exchanges) and 0 otherwise. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Chapter 5

Conclusion

The aim of this thesis was to appraise various political and institutional aspects of stock return dynamics. It thereby contributes to a lively debate in the recent finance literature and bridges a gaping chasm between the available empirical evidence and the informational requirements of practitioners and academia alike. The findings are presented in five self-contained essays that are grouped in three broader yet speciated chapters. Specifically, the investigation embraces the following elements: political patterns in stock market returns, stock market volatility around elections, and the impact of institutional investors' trading activities on stock market efficiency.

The opening chapter, "Political Cycles in Stock Market Returns", consists of two essays that shed light on the international pervasiveness of political stock market anomalies. Recently, two paradoxes have been affirmed to hold on U.S. stock markets: the Democrat premium (Santa-Clara and Valkanov (2003)), implying higher returns under Democratic administrations, and the presidential cycle effect (Booth and Booth (2003)), imposing a pronounced election cycle on security returns. The persistence of these patterns presents a serious challenge to the Efficient Market Hypothesis (EMH). Since both irregularities have been studied extensively for the U.S. but not yet on a global scale, the call for international evidence was eminent. Moreover, overcoming the single-country approach adopted in prior studies proves beneficial from the statistical point of view as more powerful econometric testing is possible.

The first essay in this chapter, therefore, investigates the relation of political cycles and stock returns in an international data set covering the 15 largest mature stock markets in terms of market capitalization. In addition to an empirical analysis of a broad sample of individual countries, this setup allows for the application of a panel framework. The results suggest that the aforementioned anomalous cyclical patterns are not strikingly pervasive global phenomena but rather limited to the U.S. and few other incidences. This finding is robust and valid after controlling for business cycle fluctuations. The panel regressions do not support either of the two anomalies, lending some support to the notion of informational efficiency with regard to politically-induced factors. The second essay explicitly takes into account that an aggregate analysis based on monthly data might still not be sufficient to capture the return dynamics around and in-between elections. Thus, a further test based on daily data and comprising 24 OECD countries is presented. The evolution of returns around Election Day is scrutinized in an event-study framework, funnelling into the conclusion that there are no significant abnormal returns to achieve around election dates. Furthermore, the results in the first essay are buttressed in that statistically significant return differentials between the tenures of left-wing and right-wing governments are hard to detect. Consequently, international investment strategies based on the political orientation of countries' leadership are likely to be futile.

The following chapter, "Stock Market Volatility around National Elections", shifts focus from the first to the second moment of return distribution and investigates whether the event of a national election induces higher stock market volatility in a sample of 27 OECD countries. It is found that the country-specific component of index return variance can easily double during the week around the election, which attests to the fact that investors are surprised by the actual election outcome. Several factors like narrow margin of victory, lack of compulsory voting laws, change in the political orientation of the government, or the failure to form a coalition with a majority of seats in parliament significantly contribute to the magnitude of the election shock. These findings have important implications for the optimal strategies of risk-averse stock market investors and participants of the option markets: While the former can expect higher utility from diversifying their portfolios internationally due to low premia for bearing the election risk in their home country, the latter could design some profitable volatility-based trading strategies. Moreover, our results are of topical interest to pollsters since the large election surprise indicates room for further improvements.

Finally, the last chapter, "Institutional Investors and Stock Market Efficiency", is compounded by two studies that assess the impact of institutional trading on stock market efficiency. The evidence provided in this chapter helps resolve an ongoing academic controversy on the ultimate effect of institutional investors' trading activities.

A priori, large pension or investment funds might move security prices *towards* greater efficiency through their better informedness or *away from* it through peculiarities in their trading behavior. The Polish and Hungarian emerging stock markets provide an interesting institutional setting to explore this issue because their history encompasses periods of predominately individual trading as well as increased institutional trading. In both countries, pension system reforms in the late 1990s and an associated increase in investment activities by large pension fund investors provide a natural experiment to investigate the impact of increased institutional trading on stock returns.

The first essay in this chapter utilizes the unique institutional characteristic described to provide evidence on the impact of institutional versus individual investors on the January stock market anomaly. Robust empirical results suggest that the increase in institutional ownership has reduced the magnitude of an anomalous January effect previously induced by the trading behavior of individual investors. The second essay addresses the implications of payment patterns on the Monday effect and the turn-of-the-month stock market anomaly. Again, the consequences of a changing investor structure are subjected to scrutiny. We find robust empirical evidence in favor of abnormally high stock returns on the first Mondays of the month and the trading days around the turn of the month. This pattern is consistent with the payment schemes in both countries and more pronounced during the period of predominately individual trading. Hence, the hypothesis that increased institutional trading leads to higher informational efficiency is supported.

Summing up, this thesis carried out a thorough analysis of relevant political and institutional factors with a bearing on stock return dynamics. At the end of the day, the factors considered do not seem to require the general rejection of the basic premise of efficient markets, a comforting result for the proponents of the EMH. Nonetheless, challenges for future research are abundant and clamant, particularly at the interface between political economy and finance. Clearly, moving beyond aggregate stock market indices to the richer information in the cross-section of returns seems worthwhile, along the path Knight (2007) starts down. Another promising extension lies in the exploration of high-frequency data to gain a better understanding of market dynamics in response to political news (Snowberg, Wolfers, and Zitzewitz (2007)). The emergence of liquid prediction markets increasingly devoted to the coverage of political events does come in handy towards realizing this aspiration.

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