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Seasonality and the Non-Trading Effect on Central European Stock Markets

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1. Introduction

The analysis of seasonal patterns in the behavior of stock-market returns has been of considerable interest during recent decades. The reason behind this curiosity remains clear: any predictable pattern in stock returns and variances may provide investors with returns in excess of the stock-market average or from a specific portfolio benchmark. Also, seasonality on equity markets is an anomaly inconsistent with the efficient market hypothesis and is thus interesting *per se*.

It has been observed in numerous studies that the distribution of stock returns may be different across the days of the week (day-of-week effect) and/or between days following a non-trading period and days following a trading day (non-trading effect). Specifically, French (1980), Keim and Stambaugh (1984) and French and Roll (1986) were among the first to confirm the weekend effect, i.e. significantly negative returns on Mondays on the US stock market. Kim (1988) reports similar findings for the UK and Canadian stock markets, while Jaffe and Westerfield (1985) confirm significant seasonality on the Japanese and Australian equity markets, although here the lowest average returns occur on Tuesdays rather than Mondays. With regard to the emerging markets, Wong et al. (1992) find the day-of-week effects on the Southeast Asian stock markets with significant negative returns occurring on Mondays and Tuesdays. Damodaran (1989) argues that the weekend effect in the US is caused by the fact that most bad news arrives after the closing of stock markets on Friday. Since it is widely assumed that the US market significantly influences stock markets in other countries, this hypothesis can also explain the negative stock returns on Mondays and Tuesdays in Japan and Australia which occur partially with a lag one due to the time difference. Another cause for the Monday effect advocated by, e.g., Foster and Viswanathan (1990) is that on Mondays there is supposedly more news to process and evaluate than on other trading days. According to Lakonishok and Maberly (1990), however, trading tends to be less intensive on Mondays with the feature that individual investors tend to sell more than institutional investors do resulting in large

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supply and declining prices. Yet another explanation advanced by behavioral finance is that Monday is the worst day of the week for investors because it is the first working day of the week and consequently investors tend to be more pessimistic and are more inclined to sell on Mondays than on other trading days.

The earlier studies discussed above focus solely on the differences in the unconditional mean stock return across the days of the week. In light of the recent voluminous literature documenting the time-series predictability of stock returns,[1] the focus should naturally shift to studying conditional returns instead. One approach to this end is to apply the periodic autoregressive model (PAR) which allows the autoregressive parameters to vary with the day of the week. This model is considered in Bessembinder and Hertzel (1993) and Abraham and Ikenberry (1994). In these two papers, the day-of-week correlation in US stock returns is modeled using the PAR framework while volatility is held constant across the days of the week. Their main result is that autocorrelation is significant only on Mondays and Tuesdays, being positive on Mondays and negative on Tuesdays. Coupled with significantly positive unconditional return on Monday, this implies overreaction on Monday which tends to be corrected on Tuesday. This finding is later confirmed in (Franses – Paap, 2000).

Besides the conditional mean, periodic time-series models have also been applied to the analysis of seasonality in the volatility of stock returns. Bollerslev and Ghysels (1996) use a periodic GARCH model (PGARCH) coupled with a PAR model for the mean to study the non-trading effect in exchange rates, while Franses and Paap (2000) employ PAR-PGARCH to investigate seasonality in the returns of the S&P 500 index. Such a combination provides a better understanding of the empirical aspects of the problem. It is also compatible with the classic portfolio theory in that any rational decision maker with a risk-averse attitude should consider both returns and variances of financial assets when forming an investment portfolio. Moreover, as Osborn (1991) shows, neglecting periodic autoregressive behavior would spuriously suggest seasonal heteroskedasticity implying that both the conditional mean and conditional volatility should be jointly analyzed using periodic models.

The purpose of this paper is to apply the PAR-PGARCH methodology to study the seasonality and the non-trading effect on the Central European stock markets. In particular, we focus on the Czech, German, Hungarian and Polish markets represented by corresponding market indices and cover the period from January 1997 to June 2004. We hope to provide new empirical evidence regarding seasonality on emerging equity markets and compare it to existing results from both developed and developing markets.

The rest of the paper is organized as follows: The next section provides a brief overview of the methodology, along with a brief discussion of the theoretical properties of the model. Specific econometric issues related to the estimation are also explained. Section 3 presents data on stock returns from the Czech Republic, Hungary, Poland, and Germany and contains some ele-

[1] See (Campbel et al., 1997) and the references therein.

mentary descriptive statistics to accompany the estimation results in the section that follows. Section 4 then summarizes the empirical findings and Section 5 concludes the paper. We include the German DAX stock-market index to compare the results from the Central European countries to a standard western developed market.

2. Methodology

In this paper, we employ the PAR-PGARCH model introduced in (Franses – Paap, 2000) to investigate the seasonality in daily returns on Central European stock markets. Denoting by P_t the value of the stock market index at time t, the PAR(p)-PGARCH(1,1) model for the continuously compounded stock returns $y_t = 100 \cdot [\log(P_t) - \log(P_{t-1})]$ is given by:

$$y_t = \mu_s + \sum_{i=1}^{p} \phi_{is} y_{t-i} + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \eta_t \sqrt{h_t}, \; \eta_t \sim N(0,1) \tag{2}$$

$$h_t = \omega_s + \beta h_{t-1} + \alpha_s \varepsilon^2_{t-1} \tag{3}$$

where $s = 1, 2, 3, 4, 5$ denotes the day of the week. As opposed to the usual AR-GARCH model, the parameters in a PAR-PGARCH model are allowed to vary with the day of the week. This specification is suitable for modeling seasonality in the mean as well as volatility of daily returns. The model can also capture the differences in the degree of predictability of stock returns and the persistence of variance across the days of the week. Following Bollerslev and Ghysels (1996) and Franses and Paap (2000) we specify the PGARCH equation (3) with only α_s varying as this turns out to be convenient for estimation purposes.

The stationarity conditions for the mean process given in equation (1) can be derived by rewriting the PAR model as a vector autoregressive model. Stacking the daily observations into a weekly observed vector $\boldsymbol{y}_t = (y_{1T}, \ldots, y_{5T})$, where y_{sT} is the observation on day s in week T, the PAR(p) model has the following alternative representation:

$$\boldsymbol{A}_0 \boldsymbol{y}_T = \boldsymbol{\mu} + \boldsymbol{A}_1 \boldsymbol{y}_{T-1} + \boldsymbol{A}_2 \boldsymbol{y}_{T-2} + \ldots + \boldsymbol{A}_m \boldsymbol{y}_{T-m} + \boldsymbol{\varepsilon}_T \tag{4}$$

where $\boldsymbol{\mu}$ contains the stacked seasonal constants, $\boldsymbol{\varepsilon}_T$ is a vector white-noise process containing the stacked $\boldsymbol{\varepsilon}_t$ variables and the number of lags m depends on p.[2] The VAR model in (4), and hence the PAR model in (1), is stationary provided that the roots of the characteristic equation:

$$\left| \boldsymbol{A}_0 \boldsymbol{z}^m - \boldsymbol{A}_1 \boldsymbol{z}^{m-1} - \boldsymbol{A}_2 \boldsymbol{z}^{m-2} - \ldots - \boldsymbol{A}_m \right| = \boldsymbol{0}$$

lie inside the unit circle. For a simple PAR(1) model that will be estimated later on in this paper, $m = 1$, the matrices $\boldsymbol{A}_0, \boldsymbol{A}_1$ are given by:

[2] For $p \leq 5$, $m = 1$, for $5 < p \leq 10$, $m = 2$, and so on.

$$
\boldsymbol{A}_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ -\phi_{12} & 1 & 0 & 0 & 0 \\ 0 & -\phi_{13} & 1 & 0 & 0 \\ 0 & 0 & -\phi_{14} & 1 & 0 \\ 0 & 0 & 0 & -\phi_{15} & 1 \end{bmatrix} \qquad \boldsymbol{A}_1 = \begin{bmatrix} 0 & 0 & 0 & 0 & \phi_{11} \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}
$$

and the stationarity condition reduces to $\phi_{11}\phi_{12}\phi_{13}\phi_{14}\phi_{15} < 1$. The stationarity conditions for the variance process given in (3) can be obtained in a similar way – see, e.g., (Franses – Paap, 2000) for details. The PGARCH process is periodically stationary provided that

$$
\prod_{i=1}^{s} (\alpha_s + \beta) < 1
$$

If, on the contrary, $\Pi_{i=1}^{s}(\alpha_s + \beta) = 1$, the process is called periodically integrated (Franses – Paap, 2000).

Assuming normal distribution of innovations η_t, the PAR-PGARCH model will be estimated by the method of maximum likelihood using the BHHH algorithm. To do this, we rewrite the equations (1) and (3) using day-of-week dummy variables D_{st}, with $s = 1, 2, 3, 4, 5$, as follows:

$$
y_t = \sum_{s=1}^{5} D_{st} \, (\mu_s + \sum_{i=1}^{p} \phi_{is} y_{t-i}) + \varepsilon_t \tag{5}
$$

$$
h_t = \sum_{s=1}^{5} D_{st} \, (\omega_s + \alpha_s \varepsilon^2_{t-1}) + \beta h_{t-1} \tag{6}
$$

The initial conditions for MLE can be obtained in the usual way by running OLS on equation (5).[3] Since there is mounting evidence on the non-normality of stock returns, we use the Bollerslev and Wooldridge (1992) robust standard errors to draw statistical inference.

Having found and estimated a satisfactory PAR-PGARCH model for stock returns, we will run likelihood ratio tests of seasonality of the mean or variance or both. In particular, we consider the following set of hypotheses for the mean process:

$$
H_1^M: \; \phi_{is} = \phi_i \; \forall s
$$
$$
H_2^M: \; \mu_s = \mu \text{ and } \phi_{is} = \phi_i \; \forall s
$$

and for the variance process

$$
H_1^V: \; \alpha_{is} = \alpha_i \; \forall s
$$
$$
H_2^V: \; \omega_s = \omega \text{ and } \alpha_{is} = \alpha_i \; \forall s
$$

[3] The lag length p in equation (5) is determined by Akaike information criteria and the Ljung--Box Q test for residual autocorrelation prior to MLE.

These hypotheses are similar to Franses and Paap (2000), and are related to the day-of-week effect on the mean and volatility of returns. As in (Bollerslev – Ghysels, 1996), we might also be interested in the behavior of stock returns on days following non-trading days. These include weekends, holidays and other days on which the market is closed. For ease of interpretation, we re-parametrize the PAR-PGARCH model as follows:

$$y_t = (\mu + \mu_N D_t^N) + \sum_{s=1}^{5} (\phi_i + \phi_{iN} D_t^N) y_{t-i} + \varepsilon_t \tag{7}$$

$$h_t = (\omega + \omega_N D_t^N) + (\alpha + \alpha_N D_t^N)\varepsilon_{t-1}^2 + \beta h_{t-1} \tag{8}$$

where D_t^N is a dummy variable that has a value of one at time t if the market was closed at t–1 and zero otherwise. We then have the following hypothesis for testing the non-trading effect on mean and volatility of stock returns:

$$H_{1'}^M : \phi_N = 0$$
$$H_{2'}^M : \mu_N = \phi_N = 0$$

$$H_{1'}^V : \alpha_N = 0$$
$$H_{2'}^V : \omega_N = \alpha_N = 0$$

The simple hypotheses $H_{1'}^M$ and $H_{1'}^V$ will be tested using the usual t-ratio which is asymptotically standard normal, while the remaining joint hypotheses will be tested using the usual likelihood ratio test. The LR test statistics have asymptotically χ^2 distribution with the number of degrees of freedom equal to the number of parameter restrictions under the null hypothesis.

3. Data Description

We perform the analysis using daily returns on the following market indices: DAX (Germany), BUX (Hungary), PX-D (Czech Republic) and WIG20 (Poland). All indices contain the most liquid stocks from the corresponding markets and hence the problem of spurious autocorrelation induced by non-synchronous trading should not arise – see (Lo – MacKinlay, 1990) for the implications of non-synchronous trading. We focus on a seven-and-a-half year period starting in January 1997 and ending in June 2004, except for the Czech PX-D index, which was first calculated in September 1997. The data were obtained from the Bloomberg database and from the Prague Stock Exchange.

Table 1 reports descriptive statistics for continuously compounded daily returns on the above mentioned market indices.

Except for BUX (Hungary), the summary statistics are very similar across the indices. This may indicate that there is not a large disparity between the Central European and the western stock markets. For all four indices, the Jarque-Bera statistics are highly significant and point at non-norma-

TABLE 1 Descriptive Statistics

	DAX	BUX	PX-D	WIG20
No. of obs.	1,888	1,861	1,714	1,863
Mean	0.017	0.054	0.021	0.008
St.Dev.	1.800	1.959	1.742	1.890
Maximum	7.553	13.61	7.538	7.647
Minimum	–8.875	–17.89	–10.38	–10.32
Skewness	–0.188	–1.001	–0.285	–0.142
Kurtosis	4.817	15.31	5.107	4.990
Jarque-Bera	271.06*	12,065.4*	340.5*	313.95*

Note: *significant on 1% level

TABLE 2 The Day-of-Week Effect

Day	Par.	Index			
		BUX	DAX	PX-D	WIG
Monday	μ_1	0.221*	0.171	0.050	0.102
	ϕ_1	0.170*	–	0.234*	0.251*
	ω_1	0.353	0.098	0.185	0.502
	α_1	0.187*	0.098*	0.122*	0.132*
Tuesday	μ_2	–0.078	0.024	–0.031	–0.105
	ϕ_2	0.061	–	0.121	0.016
	ω_2	–0.024	–0.138	0.128	0.247
	α_2	0.287*	0.081*	0.115*	0.057
Wednesday	μ_3	0.068	0.014	0.014	–0.146
	ϕ_3	0.073	–	0.110	0.001
	ω_3	0.349	0.102	0.301	–0.281
	α_3	0.126*	0.102*	0.127*	0.128*
Thursday	μ_4	0.049	0.063	0.202*	0.167
	ϕ_4	0.125	–	–0.055	0.073
	ω_4	–0.208	0.301	0.045	0.483
	α_4	0.131*	0.058	0.060*	0.054
Friday	μ_5	0.159	0.078	0.104	0.106
	ϕ_5	–0.028	–	0.099	0.174*
	ω_5	0.227	–0.088	–0.305	–0.209
	α_5	0.080*	0.152*	0.108*	0.140*
	β_1	0.806*	0.885*	0.873*	0.358
	β_2	–	–	–	0.495*
Q (10)		8.813	6.740	8.626	4.895
Q^2(10)		8.102	17.24	10.53	3.988

Note: * significant on 1% level

lity of distributions of the corresponding daily stock returns – see, e.g., (Vošvrda – Žikeš, 2004) for empirical investigation of conditional distributions of CE stock returns.

4. Empirical Results

In *Table 2* the estimated values of all relevant parameters from the equations (5) and (6) are presented. Due to the large number of observations we set the level of statistical significance to 1 %. Testing for autocorrelation up

TABLE 3 Seasonality Tests

		BUX	DAX	PX-D	WIG
H_1^M	$\chi^2(4)$	7.35	–	13.78*	13.94*
H_2^M	$\chi^2(8)$	17.68	2.67	18.50	25.79*
H_1^V	$\chi^2(4)$	17.96*	4.69	3.19	6.84
H_2^V	$\chi^2(8)$	27.65*	10.04	11.40	17.98

Note: * significant on 1% level

to ten lags in the standardized residuals and squared standardized residuals, the $Q(10)$ and $Q^2(10)$ statistics are statistically insignificant for all four indices. This implies that all models have been properly specified and thus adequately describe the variation in the conditional mean and variance of stock returns.

Focusing on the first parameter, μ_s, only the BUX (Hungary) market index generates an estimate which is significantly different from zero on Monday. With one exception – PX-D (Czech Republic) on Thursday – no other constant (μ_s) estimates are found statistically significant. As for the estimates of the first-order correlation in daily stock returns, we notice that they are significant at the 1% level on Monday for all three Central European indices. In addition, the estimates prove to be significant for Friday's returns on WIG (Poland). Since the unconditional mean for Monday's return is given by $\mu_1 / (1 - \phi_1)$, our estimates indicate the presence of the Monday effect in the returns on Hungarian stocks. Comparing our results to those of Franses and Paap (2000), Bessembinder and Hertzel (1993) and Abraham and Ikenberry (1994), who all focus on the U. S. market, we observe a similar pattern in autocorrelation on Mondays but find neither negative nor statistically significant autocorrelation in CE stock returns on Tuesday. Thus, the overreaction on Monday that tends to be corrected on Tuesday observed on the U. S. market does not occur on the CE stock markets.

Observing the table further, we note that the estimates of both α_s and β are almost always different from zero at the 1% level of significance. This could in fact lead us to reject those models that assume constant volatility over days of the week. Note also that the negative estimates of ω_s in some cases need not necessarily imply negative conditional variance as Franses and Paap (2000) show. Indeed, the estimated conditional variance of all indices never becomes negative over the whole sample period we use.[4] It is difficult to deduce any common pattern in the persistence of volatility across the days of the week (α's) from our estimates. It appears that the behavior of volatility changes with the day of the week but the highest value occurs on different days for different indices. Thus no particular day-of-week effect in volatility can be inferred from the estimates in Table 2.

Table 3 shows the results of testing for the presence of seasonality in the mean (H^M) and the variance (H^V) processes as described by equations (5) and (6), respectively. The test statistics corresponding to each of the four

[4] The proof of this claim is not included here for the sake of brevity. It is available from the authors upon request.

TABLE 4 Tests of Non-Trading Effect

Day	Par.	Index			
		BUX	DAX	PX-D	WIG
Trading	μ	0.083	0.054	0.077	0.008
	ϕ	0.084*	–	0.065	0.062
	ω	0.188*	0.060	0.081	0.114
	α	0.212*	0.106*	0.104*	0.106*
Non-trading	μ_N	0.015	0.080	–0.032	0.080
Effect	ϕ_N	0.019	–	0.157	0.166*
	ω_N	–0.033	–0.015	–0.054	0.166
	α_N	–0.113*	–0.006	0.007	0.026
	β_1	0.771*	0.877*	0.873*	0.354
	β_2	–	–	–	0.489*
Q(10)		8.104	6.262	8.826	5.711
$Q^2(10)$		8.263	18.068	13.921	6.039

Note: *significant on 1% level

hypotheses are distributed as χ^2 with $p(s-1)$, $(p+1)(s-1)$, $(s-1)$ and $2(s-1)$ degrees of freedom under the null hypothesis, respectively.

In the case of BUX, the hypothesis of no seasonality in the mean is sustained while the hypothesis of non-seasonal variance is rejected. In other words, the non-seasonal autoregressive behavior of its daily stock returns is consistent with the data and the model used in our estimation effectively reduces to the simpler PGARCH model of Bollerslev and Ghysels (1996) with a non-seasonal AR equation for the mean. Thus the apparent Monday effect in Hungarian stocks implied by the estimates in Table 2 does not find further empirical support. On the contrary, seasonality in the variance process is confirmed by the likelihood ratio tests. Turning to DAX, none of the day-of-week effect hypotheses is rejected and thus the existence of the Monday effect suggested by the statistically significant estimate of μ_1 does not sustain further testing. On both PX-D and WIG, the presence of seasonalities in the mean is verified. However, the hypothesis of no seasonality in the variance process cannot be rejected for either of the two indices. Thus, for PX-D and WIG the variance part of the model becomes a non--periodic GARCH model.

Turning to the analysis of the non-trading effect, *Table 4* summarizes the estimates of the PAR-PGARCH models given in equations (7) and (8). The results imply significant non-trading effect in the mean of returns on the WIG index. This is not surprising as significant positive autocorrelation was found for Mondays (see Table 2) and Mondays account for more then 80 % of the days following non-trading days in our sample. On the contrary, we find significantly lower persistence in volatility on such days for the Hungarian BUX index although the persistence of volatility on Mondays seems to be rather higher (see Table 2). To shed more light on the non--trading effect we perform the likelihood ratio tests for the non-trading effect hypothesis outlined in Section 3.

Table 5 reports the results of these likelihood ratio tests. We obtain further evidence of the non-trading effect in the mean of the Polish stock returns. No anomalies are found in the returns on the German DAX,

TABLE 5 Testing Non-Trading Effect

		BUX	DAX	PX-D	WIG
$H_{1'}^{M}$	$\chi^2(1)$	0.10	–	5.92	6.80*
$H_{2'}^{M}$	$\chi^2(2)$	0.15	0.98	5.99	7.81
$H_{1'}^{V}$	$\chi^2(1)$	6.49	0.02	0.12	1.27
$H_{2'}^{V}$	$\chi^2(2)$	7.07	0.06	0.17	2.35

Note: *significant on 1% level

Hungarian BUX and the Czech PX-D indices. Combining these results with those from seasonality testing we get a fuller picture of the behavior of the CE stock returns across the days of the week. Clearly, except for the Polish WIG index, what drives the daily conditional distributions of stock returns is seasonality and not the non-trading effect. In the case of BUX the seasonality occurs in the variance process, with the conditional variance being largest on Mondays and most persistent on Tuesdays. For the Czech PX-D and the Polish WIG indices we find seasonality in the conditional mean with the highest autocorrelation occurring on Mondays. As for the Polish WIG index, it is difficult to disentangle the effect of seasonality and the non-trading effect in the conditional mean from our results. As we already mentioned above, since Mondays account for more then 80 % of the days following non-trading periods, the differences in the conditional distributions of Polish daily returns cannot be attributed to either seasonality and/or non-trading effect without further research. To this end we could employ an even more complicated PAR-PGARCH model with coefficients changing both with the day-the-week as well as with trading or non-trading on the previous day. We do not address this issue in this paper, however, and leave it for future research.

5. Conclusion

In the empirical finance literature, seasonality effects have been studied extensively in both equity and foreign exchange markets. Still, the analysis of seasonal patterns on stock markets in Central Europe has found its way to only a limited number of research papers. The paper at hand extends this empirical work in several ways. It investigates the seasonality and the non-trading effect on Czech (PX-D), Polish (WIG) and Hungarian (BUX) stock indices within the framework of periodic autoregressive models for both the mean and variance of stock returns suggested in (Franses – Paap, 2000). Our results provide evidence of significant day-of-week effects in the mean of Czech and Polish stock returns with Monday being the day on which stock returns tend to be most persistent. In addition, a significant seasonality has been found in the volatility of the Hungarian BUX index, where the highest unconditional volatility occurs on Mondays, whereas it is most persistent on Tuesdays. In a similar way, we find significant non-trading effect in the mean of the WIG stock indices.

It is worth emphasizing that the predictability and seasonality of stock returns found in this paper need not imply market inefficiency. Although our results can be useful in the real-world investment process, they do not imply that profitable trading strategies yielding superior returns when adjusted for transaction costs exist. A further investigation into the economic (and not only statistical) significance of the predictability and seasonality of stock returns on Central European stock markets is therefore called for.

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SUMMARY

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Seasonality and Non-Trading Effect on Central European Stock Markets

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This paper investigates seasonality and non-trading effects on central European stock markets within the framework of a periodic autoregressive model for both the mean and the volatility of stock returns. The authors find significant day-of-week effects in the mean of returns on the Czech PX-D and the Polish WIG indices, and significant seasonality in the volatility of the Hungarian BUX index. Similarly, the authors' empirical results indicate the presence of the non-trading effect in the mean of WIG stock returns. The seasonal patterns in central European stock indices cannot, however, be attributed to any particular day-of-week effect.