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The calendar anomalies on Warsaw Stock Exchange

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Abstract

Calendar anomalies are defined as any seasonal tendency that occurs in stock markets on a monthly, daily or intra-daily basis. This paper is an attempt to verify if selected calendar effects are present on the Warsaw Stock Exchange (WSE) for each level of data aggregation and to compare their strength in the case of big cap and small cap listed companies, as well as the main indices. I use daily data from 2014–2019 for stock market indices and randomly chosen companies listed on the WIG20 and the sWIG80 and intraday data from March to June 2019 for the same companies. Later, I employ Markov--switching GARCH models in order to verify seasonal effects of each frequency. The conducted research proved that seasonal anomalies are present on the WSE but they mainly concern small cap companies and indices on which they are listed. On the basis of the obtained results I try to identify triggers of the calendar anomalies on the WSE.

Keywords: calendar anomalies, behavioural finance, MS-GARCH models, Warsaw Stock Exchange

JEL: G14, G40

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1 Introduction

Every anomaly or seasonal tendency on the stock market related to the calendar is the calendar effect or calendar anomaly. In efficient markets in terms of Fama definition (1970) calendar anomalies should not exist. There are lots of studies that prove markets inefficiency as well as calendar effects – seasonal, monthly, daily or intra-daily. An important observation has been made that the more liquid the assets the fewer anomalies can be found. That is why the aim of the present paper is to verify if calendar anomalies occur on the WSE in general, for indices, as well as for small and big companies separately.

There are many reasons for calendar anomalies, e.g. market inefficiency, taxation, mental accounting (based on Kahneman and Tversky prospect theory) or even the lunch effect (Będowska--Sójka 2013). The known effects of these anomalies include e.g. the possibility to earn excess returns. The question is for how long and how much should investors earn to identify the observed effect as an anomaly (Czerwonka, Gorlewski 2012). From the statistical point of view anomalies can be explained by correlation and seasonality in the data. The seasonal effects observed in the financial data can last for longer (multi-year or monthly effects) or shorter (daily or intra-day effects) periods and can be linked to volatility clustering. More on volatility clusters can be found in Doman and Doman (2009). This paper aims to verify the effects of various frequencies (month-of-the year, day-of-the week, hour--of-the day), that is why MS-GARCH models are employed in order to indicate volatility jumps that can be explained with calendar anomalies.

The volatility clusters related to calendar anomalies mentioned in the previous paragraph are closely related to the liquidity of assets. Calendar anomalies for the most liquid capital markets began to decline with the analysis of the 1990s data onward (Schwert 2002), while for smaller markets, like the WSE, they were confirmed even for the 2011–2016 period (Zawadzki, Troska, Domańska 2017). On the other hand, most of the anomalies are assigned to the non-rational individual investors' behaviour and for that reason it should be more visible in non-liquid asset quotations as institutional investors are not interested in including it in their portfolios. To verify stated relationship between calendar anomalies and liquidity the research compares small and big cap companies listed on the WSE.

2 Literature review on calendar anomalies

The literature on calendar anomalies is very wide-ranging and can be dated back to 1940s (Wachtel 1942). Most of the discussion on month-of-the year effect took place in the 80s and 90s thanks to works by Reinganum (1983), Haugen and Lakonishok (1988), Keim (1983), Roll (1981) and Banz (1981). Most of the research proved that there are statistically significant higher returns in January than any other month (3% vs 0.5% in other months according to Wachtel). It was an important finding for the purposes of this paper that effect of the month can be linked to market capitalization of the companies, especially small-cap ones (Banz 1981; Reinganum 1983; Hull, Mazachek, Ockree 1998). This was also proved by Gultekin and Gultekin (1983) for various markets. The explanation of the effect was mainly taxation (Reinganum 1983; Gultekin, Gultekin 1983) and cash allocation (Ritter 1988). Szyszka (2009) explains the January effect with the anchoring bias, which is one of the main elements of the Prospect Theory by Kahneman and Tversky (1979). What is more, Gu (2003) and Schwert (2002) suggested that month-of-the year effects have become less visible from the 80s on. Research on seasonal effects on the

WSE was conducted by Galus (1997) and Szyszka (2003). Świder (2019) provided interesting finding on month-of-the year effect existence on the WSE for the 1995–2017 period, identifying their non-lasting behaviour. Zawadzki, Troska and Domańska (2017) proved the existence of January effect and "sell in May and go away" effect on the WSE for 2011–2016. Budka, Kosiński and Sobczak (2017) also confirmed the January effect for the WIG-food index.

Another important calendar effect that is widely discussed is the day-of-the week anomaly. This effect is mainly related to returns on Mondays and Fridays. Early research proved lower returns on Mondays (French 1980; Smirlock, Starks 1986; Lakonishok, Maberly 1990) but some of them were repealed by the research of the 1980s and 1990s data (Schwert 2002). Some of the researchers shifted this effect from Monday to Tuesday (Chang, Pinegar, Ravichandran 1993). Szyszka's (2003) research on Polish market data did not prove any day-of-the week anomaly, a conclusion later supported by Budka, Kosiński and Sobczak (2017). Conversely, the research conducted by Landmesser (2006) for four WSE indices and the four biggest companies listed on the WSE in 2002–2005 proved statistically significant higher returns on Mondays and Fridays, but not high enough to cover the transaction fees. The existence of day-of-the week anomaly for the main WSE indices was later proved by Zawadzki, Troska and Domańska (2017) for 2011–2016. One of the most significant explanations of the day-of-the week effect was given by Damodaran (2007) stating that companies tend to reveal bad information on Fridays after the session closes as that weakens investors' reactions on Monday. Borowski (2017) carried out interesting research, where he tested for anomalies during unfortunate dates (like Friday 13) and proved their existence on the WSE.

Seasonal effects can also be found in the intraday data. The mentioned research by Smirlock and Starks (1986) also provided the analysis of hourly distributed returns showing that Monday negative returns occur in the first hour of trade while during the rest of the week they tend to be positive. There is also a more detailed analysis from Harris (1986) that assigns this effect to the first 45 minutes of the trading on Monday. Another interesting finding is the U-shaped daily pattern found on the Polish market by Będowska-Sójka (2013). This effect is sometimes called the lunch effect. The idea of intraday anomalies can be explained by market microstructure, especially market frictions. More on the market microstructure can be found in Doman (2011).

This paper aims to refer to the cited studies by analysing the WSE data from 2014–2019 and to verify if seasonal effects are present on the Polish market. As was previously mentioned, calendar effects can be stronger for illiquid assets, that is why the research has been thought out to compare carefully all of the effects for small- and large-cap companies. The relation between calendar anomalies and illiquidity can be inferred mainly from the decline of such anomalies on the most developed capital markets. Every effect analysed in this paper is introduced with the analysis of the effect for small- and large-cap indices in order to prove it on a higher aggregation level.

3 Markov switching GARCH models

The data used in the research consists of daily closing prices for three indices from the WSE – the WIG as the widest index, the WIG20 for anomalies analysis of the biggest and most liquid companies and the sWIG80 for smaller companies from 9 June 2014 to 6 June 2019. This gives 1247 observations for each index. For a more detailed analysis 8–9 (depending on the part of the analysis) companies from WIG20 (CD Projekt SA, DINO Polska SA, LPP SA, PKN ORLEN SA, PGE SA, PKO BP SA, PZU SA and Santander BP SA) and up to 4 from sWIG80 (ABC Data SA, BOŚ SA, Monnari Trade SA and ZEP SA) have been randomly chosen for the same period. In order to analyse intraday effects, I use the hourly data for the mentioned companies from March to June 2019. This time series consists of 558 observations for each company.

The research conducted in the paper is based on logarithmic returns given by formula (1):

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

The time series in the research is later analysed for heteroscedasticity and autocorrelation. The distribution of the returns is calculated in each case in order to specify the models used in the research.

The problem analysed in this article is related to one of the most common characteristics of the financial markets, i.e. volatility clustering. The assumption behind the research is that if the seasonal effects appear on the WSE it should be characterized by high volatility periods. Other financial data series properties are fat tails, skewness and autocorrelation.

In order to allow the model to incorporate high volatility periods, Markov-switching GARCH (MS-GARCH) models are used in the research. This class of models allows the model to depend on the regimes (Doornik 2013), i.e. low volatility for the periods without observed anomalies and high volatility for periods with seasonal effects. MS-GARCH models are closely related to hidden Markov models, in which states are unobservable.

MS-GARCH structure used in the paper was suggested by Haas, Mittnik and Paolella (2004):

$$\begin{gathered} r_t = \mu(S_t) + \mu_t \\ \mu_t = h_t(S_t)^{1/2}\,\varepsilon_t,\ \varepsilon_t \sim N[0,1] \\ h_t(S_t) = \sigma^2(S_t) + \alpha_1(S_t)\mu_{t-1}^2 + \beta_1(S_t)h_{t-1}(S_t),\ S_t = 0, \ldots, S-1 \end{gathered} \tag{2}$$

where the transition probabilities between the S states (two in this research) depend only on the previous state and are given by (Doornik 2013):

$$p_{i|j} = P\left[S_{t+1} = i | S_t = j\right],\ i, j = 0, \ldots, S-1 \tag{3}$$

where S_t is an unobserved random variable that follows a Markov chain, r_t is the mean equation, μ_t is the error and h_t is the conditional variance. In this case moving within one period from state i to state j depends on the previous state only.

GARCH models considered in the paper are of order (1,1) and have one time series for each model $h_t(S_t)$.

In the case of models estimated for indices the additional variable volume is being used as a regressor in the variance equation. The volume in the models is transformed according to equation (4):

$$vol = ln\left(\frac{vol_t}{vol_{t-1}}\right) \tag{4}$$

The models used in the paper assume only two regimes – one for low volatility and one for high volatility. This simplification may lead to finding high volatility periods that do not result from seasonal effects. That is why in every case a detailed analysis of high volatility periods is conducted. What is more, according to the obtained results there was no need to introduce third regime to the estimated models.

4 Month-of-the year effect

Month-of-the year effect is one of the best known seasonal anomalies. Numerous works from 1980s have been devoted to this subject. That is why investors had a lot of time to get aware of its presence which may lead to its disappearance over time. Indeed, there are many papers proving that this effect no longer exists in many markets.

January effect is the best known month-of-the year anomaly. The main reason for its emergence was taxation (Reinganum 1983). Some works proved that it existed even in markets where the fiscal year did not overlap the calendar year (Reinganum, Shapiro 1987).

Taking all the above into consideration, Table 1 (Appendix) presents average returns for the WIG20, the sWIG80 and the WIG from 2014–2019. All the obtained results were tested for statistical significance using a t-Student test (approximately 100 observations for each month), where the null hypothesis assumes the returns are not statistically significantly different than 0. According to the data in Table 1, a statistically significant January effect can be discerned only for the sWIG80, i.e. for relatively small and less liquid companies. The average positive return for those companies can be explained by the growing demand for those assets at the beginning of the year. What is more, returns from January happen to be one of the highest noted for the sWIG80 in the analysed period. Also sWIG80 returns for February are positive and statistically significant. May and June are other months with statistically significant negative returns, which may be a sign of corroboration for the aforementioned research. The data for the WIG20 do not reveal any statistical significance, which should not be surprising due to the afore-mentioned high liquidity of the companies listed in this index. In the case of the WIG index there is one negative and statistically significant return for May other than 0. Those results clearly show that the month-of-the year anomaly is an issue concerning mainly small and illiquid companies.

The next step of the research is based on MS-GARCH models estimated for selected indices. The purpose of this part of the research is to identify if results obtained in the first step show up in volatility with an additional variable, i.e. volume.

The models estimated for three indices are shown in Table 2. I estimated MS-GARCH models with two regimes, where GARCH models were switched between two states. The use of only two regimes reflects the idea of anomalous and non-anomalous periods intertwining and makes it imperative to manually identify any high volatility periods (clusters) occurring in the data as the ones displaying calendar anomalies.

Transition probabilities for the models are given in Table 3. Columns depict the given current states and rows shows the regimes of the next state, so that Regime 1, t and 1, $t + 1$ gives the probability of staying in the same regime in the next period (P[Regime 0] in the Figures). The second regime reflects high volatility periods and is shown in Figures 1–3 for each index (Appendix). This regime should occur in December or January to reflect the seasonal effects discussed in this paragraph. Surprisingly, the transition probabilities for WIG20 and WIG suggest anti-persistence of the regimes, as the switching occur very often. This may be the case when Figures 1–3 are compared. For more liquid indices the periods of low and high volatility switch very often, while for less liquid sWIG80 regimes they prove to be more persistent. Anti-persistence was addressed by Chuffart (2015).

Only the results obtained for the sWIG80 in Figure 2 resemble seasonal anomalies related to the January effect – that is higher volatility periods for December and January. Identified volatility periods occur for the turn of 2014/2015, 2015/2016, 2017/2018, and 2018/2019. There are also high volatility periods identified within May and June which may corroborate the statistically significant data from the first part of the research (Table 1). For the WIG20 there are no high volatility periods identified within the model for month-of-the year anomalies. Interestingly, for the WIG index there is a slight volatility shift for the turn of 2014/2015 and 2016/2017 but it is not as visible, regular and long-lasting as in the case of the sWIG80. This is why on this level of data aggregation the seasonal month-of-the year anomaly can be confirmed for the sWIG80 index only.

The estimated MS-GARCH models for 8 randomly selected companies listed on the WIG20 and 4 companies listed on the sWIG80 are shown in Figure 4 and Figure 5, respectively. At this level of data aggregation month-of-the year effects were identified for CD Projekt SA (turn-of-the year – 2018, May and June effect – multiple times), LPP SA (turn-of-the year – multiple times, May and June effect – multiple times), PKN ORLEN SA (turn-of-the year – multiple times, May and June effect – multiple times), PGE SA (turn-of-the-year – multiple times, May and June effect – multiple times), PKO BP SA (turn-of-the year – 2016, May and June effect – 2016), PZU SA (turn-of-the year – 2015, 2016, May and June effect – 2015, 2016, 2018) and Santander BP SA (turn-of-the year – 2015, 2016, May and June effect – 2015) but they did not occur on a regular basis needed to prove seasonal anomalies for single assets for none of the companies.

For the companies listed on the sWIG80 multiple month-of-the-year effects were identified and they occur on a regular basis, which may lead to the conclusion that seasonal anomalies primarily affect small-cap companies. High volatility periods were identified for ABC Data SA (turn-of-the year – 2016–2019, May and June effect – 2015–2018), BOŚ SA (turn-of-the year – 2015–2019, May and June effect – 2015–2019), Monnari Trade SA (turn-of-the year – 2015–2019, May and June effect – 2015–2019) and ZEP SA (turn-of-the year – 2015, 2017, 2019, May and June effect – 2015–2019).

Comparison of the results for WIG20 and sWIG80 companies warrants the conclusion that month-of-the year anomalies may especially affect small-cap companies. In the next section we move to lower level of data aggregation to verify if the obtained results also hold on a daily basis.

5 Day-of-the week effect

The day-of-the week seasonal anomaly first discovered by French (1980) mainly affects returns on Mondays and Fridays. As Damodaran (2007) stated, companies tend to reveal negative information on Fridays which forces the investors to wait the whole weekend to take action. As a result, their reaction may be more subdued than initially planned on Friday. Another important finding is that institutional investors do not engage in trading on Fridays as they do on other days, which allows individual investors to shape the trades and lowers the volume. This anomaly has not been confirmed by researchers after 1990.

To find out if the day-of-the week anomaly is present on the WSE, I calculated returns for every weekday from 2014–2019 broken down by years. The returns were later verified using the t test (approximately 50 observations for full years for each day of the week. The obtained results are shown in Table 4. The data in Table 4 do not prove any statistically significant lower returns on Mondays. Statistically significant returns rather occur on Fridays. What is more, most of the day-of-the week effects that proved to be statistically significant occur for the sWIG80, which confirms the thesis that anomalies tend to affect mainly small-cap and rather illiquid assets.

In order to verify the significance of the day-of-the week anomaly for the whole period, calculated and verified returns are shown in the Table 5. Data in Table 5 clearly show statistically significant returns other than 0 for all indices on Fridays. It is an interesting finding that for the WIG20 and the WIG returns on Fridays are negative (while being positive on average for the rest of the week) while in the case of the sWIG80 they tend to be positive on Fridays. This different behaviour of returns for bigger companies and smaller ones listed on the sWIG80 may prove the existence of the week-of-the day effect for small-cap companies as a result of individual investors involvement in trades.

The MS-GARCH models estimated for three indices (WIG20, sWIG80 and WIG) do not reveal any repeated volatility jumps around weekdays when compared to the models presented in Section 4 of this paper. The introduction of dummy variables for each day of the week provided a positive and statistically significant variable for Friday returns for the sWIG80. Models estimated for 8 companies listed on the WIG20 are presented in Figure 4 and for the 4 companies listed on the sWIG80 – in Figure 5.

6 Intraday anomalies

Intraday anomalies on the WSE provided by Będowska-Sójka (2013) revealed a U-shaped pattern for large-cap companies. Other interesting patterns may include price duration and high volatility periods in certain times of the trading days. In order to compare the effects, I use MS-GARCH models to identify any daily patterns in hourly data for companies listed on the WIG20 and the sWIG80. The data are limited to the 7 March 2019 (Thursday) – 6 June 2019 (Thursday) period. The obtained results are presented in Figure 6 for WIG20 and in Figure 7 for sWIG80 companies. Due to lack of liquidity and missing data, the approach used in this paper made it possible to estimate the MS-GARCH model only for four companies from the sWIG80.

According to the Figures presented in Figure 6 it is not possible to find any significant patter in the hourly returns. This may be the result of too much data aggregation in one hour returns as well as to the short duration of the analysed period. Only for three of the companies from the WIG20 any high volatility regimes were identified by the estimated MS-GARCH models. Those are Dino Polska SA (Tuesdays), KGHM SA (Mondays), and Santander BP SA (Mondays). Three out of nine companies are not enough to confirm the week-of-the day effect among large-cap companies.

For the companies from the sWIG80 index no intraday patterns have been identified in this section, neither in returns nor in high volatility regimes. Interestingly, for this level of data aggregation high volatility periods were identified around all Mondays and Fridays in the dataset for all four sWIG80 companies, but unfortunately the size of the sample and the time period require further and more insightful analysis on this matter. However, the finding suggests that for small illiquid companies there may be a day-of-the week anomaly, as stated in the previous paragraph.

7 Conclusions

The research in this paper verified the presence of seasonal anomalies on Warsaw Stock Exchange in 2014–2019. The anomalies the data was tested for include month-of-the year effects, week-of-the day anomalies and intraday effects. To make the research more accurate, the analysed data included indices (WIG20, sWIG80, WIG) for both small and large cap companies as well as data for randomly chosen companies listed on the WIG20 and sWIG80. This made it possible to verify if seasonal anomalies occur more often for smaller companies as stated in literature. What is more, the data were divided into particular years as well as tested for the whole period. For the intraday effects the hourly data covered the period from March to June 2019.

Results obtained for month-of-the year anomalies show that this effect is mainly associated with small cap companies for both levels of data aggregation – for the sWIG80 index and separate companies. The results for returns analysis were confirmed with the estimated MS-GARCH models. Significant anomalies for the WIG index were not regular, which leads to the conclusion that they do not affect the whole market. The last statement may result from the weight of small cap companies in the index compared to large cap companies.

For the day-of-the week effect the analysis of the data divided into years identified regularities only for the sWIG80 index – for Wednesdays, Thursdays and Fridays (in 2019 only). There were statistically significant results for the WIG index but they were not regular. What is worth mentioning, is that for the whole data set from 2014–2019 the week-of-the day anomaly was identified in the case of all three indices – the WIG20, the sWIG80 and the WIG for Fridays, but the direction of the returns was different – positive for the sWIG80 and negative for the WIG20 and the WIG indices. The methodology adopted in this paper did not reveal any regular high volatility periods for any index, but when dummy variables introduced for each week day are taken into consideration, the variable for Friday was statistically significant for the sWIG80.

The methodology used in this research did not reveal any intraday-effects neither for the return patterns nor the high volatility regimes. For the sWIG80 companies missing data and lack of liquidity made it impossible to apply MS-GARCH models to hourly data from more companies. That is why no data of higher frequencies (i.e. 5-minute returns) were used in the third part of the research as the main purpose of the paper was to identify seasonal effects and compare them for large and small cap companies. However, the analysis of MS-GARCH models for sWIG80 companies revealed that high volatility regimes occur in hourly data around Mondays and Fridays, which warrants further analysis on that matter. What is worth mentioning, the article's main theoretical contribution is the use of MS-GARCH models to identify calendar anomalies on the WSE at each level of data aggregation for both – indices and companies.

To conclude, the conducted research proved that seasonal anomalies occur on the Warsaw Stock Exchange but they mainly affect small cap companies and the indices they are listed on, for which they exhibit the regularity condition needed for anomaly verification. For large cap companies and the indices on which they are listed the seasonal anomalies do occur but not on a regular basis, thus it may be impossible to rely on this fact to construct investment strategies and earn excess returns. The results for small cap companies and the sWIG80 suggest that calendar anomalies may be triggered by heuristics and biases of individual (non-rational) investors.

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Appendix

Table 1
Average returns for each month in 2014–2019

Month	WIG20			sWIG80			WIG		
	average return	**standard deviation**	***t***	**average return**	**standard deviation**	***t***	**average return**	**standard deviation**	***t***
January	0.0010018	0.0123818	0.8211280	0.0011176	0.0061022	1.8587099*	0.0010791	0.0102924	1.0640568
February	0.0000128	0.0107177	0.0120490	0.0014020	0.0054323	2.5937914**	0.0002626	0.0088844	0.2970588
March	0.0001854	0.0100779	0.1911980	0.0009754	0.0068135	1.4877086	0.0002279	0.0078413	0.3019988
April	0.0013180	0.0091910	1.4268240	0.0003612	0.0037757	0.9519315	0.0011257	0.0071558	1.5652381
May	-0.0021762	0.0101659	-2.1619700	-0.0008348	0.0046484	-1.8137357*	-0.0016075	0.0081871	-1.9829496*
June	-0.0010146	0.0119668	-0.8604900	-0.0021763	0.0068135	-3.2417077***	-0.0008388	0.0101582	-0.8380758
July	0.0003198	0.0096536	0.3474540	-0.0001585	0.0050276	-0.3307437	0.0007084	0.0077054	0.9641945
August	0.0009732	0.0118559	0.8490620	-0.0000515	0.0089117	-0.0597694	0.0008073	0.0103661	0.8056053
September	-0.0010119	0.0092142	-1.1359900	-0.0004318	0.0056979	-0.7838608	-0.0002005	0.0078413	-0.2644898
October	0.0000946	0.0094835	0.1050670	-0.0006677	0.0046989	-1.4971432	-0.0001821	0.0077536	-0.2474194
November	-0.0008012	0.0106313	-0.7535900	-0.0007247	0.0049926	-1.4514939	-0.0005933	0.0086474	-0.6861050
December	0.0001807	0.0120068	0.1474370	-0.0001491	0.0064973	-0.2248425	0.0000901	0.0096103	0.0919051

* indicates a 10% statistical significance, ** – 5% and *** – 1%.

Source: own calculations based on Reuters database.

Table 2
Estimated MS-GARCH models

Coefficient	**WIG20**		**sWIG80**		**WIG**	
	value	**standard error**	**value**	**standard error**	**value**	**standard error**
$\sigma_1(0)$	0.00163355	0.0007590	0.00198698	0.0003308	0.000755743	0.0006447
$\sigma_1(1)$	0.000713591	0.0009782	0.00000	0.0006739	0.00184496	0.0005390
$\alpha_1(0)$	0.0313016	0.01945	0.154517	0.06154	0.0892692	0.02472
$\alpha_1 1)$	0.0946867	0.02532	0.0559316	0.02347	0.0506409	0.02108
$\beta_1(0)$	0.960513	0.02681	0.722941	0.07885	0.748224	0.06662
$\beta_1(1)$	0.796275	0.05611	0.910329	0.03152	0.934593	0.02642

Source: own calculations.

Table 3
MS-GARCH models' transition probabilities

WIG20	**Regime 0, *t***	**Regime 1, *t***
Regime 0, *t*+1	0.28410	0.97892
Regime 1, *t*+1	0.71590	0.021080
sWIG80	**Regime 0, *t***	**Regime 1, *t***
Regime 0, *t*+1	0.95485	0.29726
Regime 1, *t*+1	0.045151	0.70274
WIG	**Regime 0, *t***	**Regime 1, *t***
Regime 0, *t*+1	0.076799	0.64795
Regime 1, *t*+1	0.92320	0.35205

Source: own calculations.

Table 4
Average returns for each day of the week in 2014–2019

	Day of the week	WIG20			sWIG80			WIG		
		average	standard deviation	*t*	average	standard deviation	*t*	average	standard deviation	*t*
2014	Monday	0.0006766	0.0071037	0.5217140	0.0008923	0.0060148	0.8125567	0.0015598	0.0060977	1.4010464
	Tuesday	0.0009846	0.0080968	0.6548400	-0.0005753	0.0053302	-0.5812132	0.0007994	0.0070439	0.6111135
	Wednesday	-0.0026770	0.0086419	-1.6393500	-0.0025910	0.0066153	-2.0725275**	-0.0021743	0.0082082	-1.4016651
	Thursday	-0.0022190	0.0085636	-1.3465400	-0.0021614	0.0058708	-1.9130373**	-0.0022094	0.0074164	-1.5479933
	Friday	0.0006672	0.0074563	0.4649860	0.0010569	0.0062643	0.8766984	0.0007688	0.0062952	0.6345779
2015	Monday	-0.0019050	0.0124102	-1.0961300	-0.0015545	0.0108847	-1.0199381	-0.0016628	0.0114940	-1.0331504
	Tuesday	-0.0019060	0.0095032	-1.4326200	0.0000727	0.0059680	0.0869771	-0.0011929	0.0076241	-1.1173699
	Wednesday	-0.0003060	0.0107960	-0.2021500	0.0014837	0.0059888	1.769314*	0.0001767	0.0088910	0.1419584
	Thursday	0.0024535	0.0120715	1.4227650	0.0014878	0.0059633	1.7464082*	0.0022324	0.0098636	1.5842672
	Friday	-0.0026520	0.0089074	-2.08433**	0.0002898	0.0056958	0.3561319	-0.0015093	0.0074435	-1.4194093
2016	Monday	0.0009531	0.0135193	0.4934760	0.0000777	0.0056013	0.0970917	0.0007689	0.0108475	0.4961686
	Tuesday	0.0013284	0.0111176	0.8449070	0.0002920	0.0041607	0.4963165	0.0015868	0.0087700	1.2794404
	Wednesday	0.0004825	0.0114951	0.2997710	-0.0003044	0.0064484	-0.3370937	0.0001618	0.0097660	0.1182823
	Thursday	0.0007960	0.0120551	0.4715540	-0.0000076	0.0057195	-0.0094569	0.0010423	0.0098050	0.7591808
	Friday	-0.0026340	0.0116705	-1.5957200	0.0014771	0.0065201	1.6019173	-0.0014135	0.0101842	-0.9814053
2017	Monday	0.0034841	0.0093723	2.602203**	0.0004999	0.0049943	0.7005983	0.0025273	0.0071356	2.4792866**
	Tuesday	0.0009112	0.0098887	0.6515410	-0.0007328	0.0054713	-0.9470233	0.0008577	0.0078857	0.7690770
	Wednesday	0.0011005	0.0106122	0.7333120	-0.0013511	0.0045784	-2.0867191**	0.0007169	0.0085789	0.5909100
	Thursday	0.0002458	0.0092739	0.1893140	0.0006209	0.0051654	0.8584831	0.0006241	0.0071916	0.6197170
	Friday	-0.0009990	0.0079140	-0.8926600	0.0014269	0.0043422	2.3236179**	-0.0005198	0.0062433	-0.5886868
2018	Monday	0.0013023	0.0102512	0.8801700	-0.0011878	0.0058352	-1.4103153	0.0004577	0.0084251	0.3763584
	Tuesday	0.0014039	0.0125691	0.7818670	-0.0019646	0.0064393	-2.1356406**	0.0006642	0.0100513	0.4625390
	Wednesday	0.0012132	0.0123698	0.6935150	-0.0014533	0.0048268	-2.1290075**	0.0012520	0.0098961	0.8945841
	Thursday	-0.0014340	0.0120101	-0.8359100	-0.0009990	0.0055774	-1.2537633	-0.0010251	0.0097695	-0.7345073
	Friday	-0.0039150	0.0118658	-2.35601**	-0.0009356	0.0051583	-1.2952432	-0.0032686	0.0098420	-2.3717182**

Table 4, cont'd

Day of the week		WIG20			sWIG80			WIG		
		average	standard deviation	*t*	average	standard deviation	*t*	average	standard deviation	*t*
2019	Monday	-0.0010590	0.0074807	-0.6489400	0.0011353	0.0052236	0.9959509	-0.0010953	0.0066909	-0.7501824
	Tuesday	0.0006560	0.0080244	0.3834390	-0.0002519	0.0043709	-0.2703209	0.0005234	0.0069663	0.3524019
	Wednesday	0.0030595	0.0090825	1.5799750	0.0015611	0.0040703	1.7988786*	0.0030380	0.0076837	1.8545187*
	Thursday	-0.0041670	0.0106811	-1.87106*	-0.0003527	0.0031617	-0.5349612	-0.0034532	0.0085485	-1.9372744*
	Friday	0.0014717	0.0085379	0.7709020	0.0021426	0.0039641	2.4171831**	0.0017810	0.0071110	1.1200930

* indicates a 10% statistical significance, ** – 5% and *** – 1%.

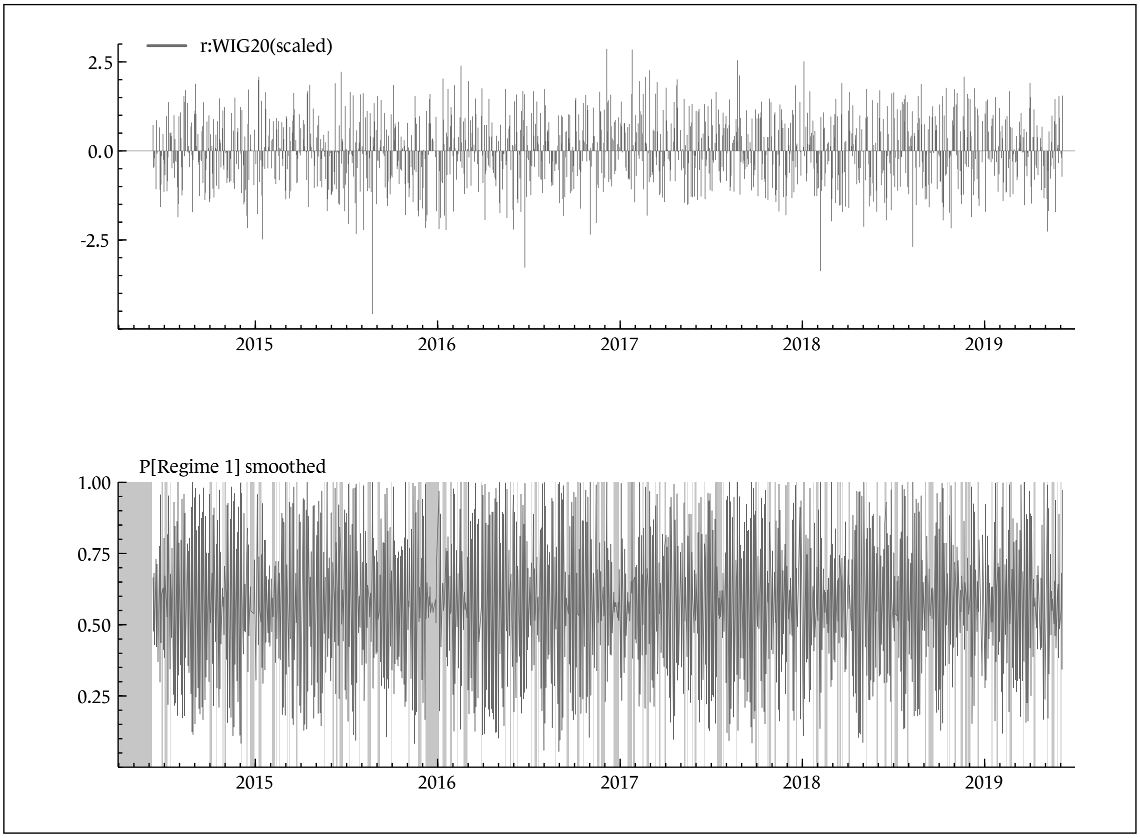
Source: own calculations based on Reuters database.

Table 5
Average returns for each day of the week in 2014–2019 for the whole period

Day	WIG20				sWIG80				WIG			
	average	standard deviation	obs.	*t*	average	standard deviation	obs.	*t*	average	standard deviation	obs.	*t*
Monday	0.0007294	0.0108524	247	1.0563129	-0.0002360	0.0069918	247	-0.5303696	0.0004895	0.0091287	247	0.8427487
Tuesday	0.0005041	0.0102995	251	0.7754158	-0.0005451	0.0054552	251	-1.5830577	0.0005125	0.0082935	251	0.9789635
Wednesday	0.0004645	0.0108782	252	0.6778348	-0.0004694	0.0058644	252	-1.2705283	0.0004828	0.0087884	252	0.8720826
Thursday	-0.0002107	0.0111315	250	-0.2993051	-0.0000449	0.0055215	250	-0.1287128	0.0000203	0.0090644	250	0.0353407
Friday	-0.0018777	0.0099038	247	-2.9797137***	0.0007412	0.0055066	247	2.1153970**	-0.0011374	0.0083168	247	-2.1493577**

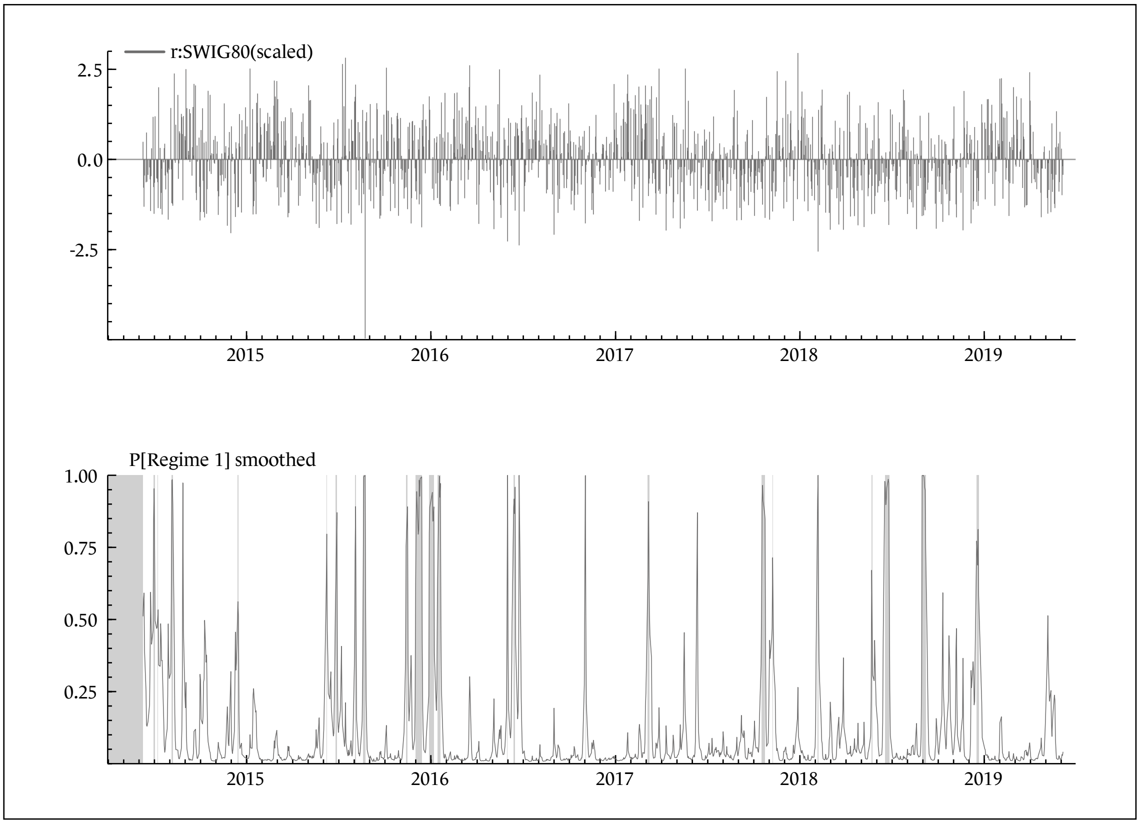
Source: own calculations based on Reuters database.

Figure 1
Daily returns and regime 1 probabilities with WIG20 regimes in 2014–2019



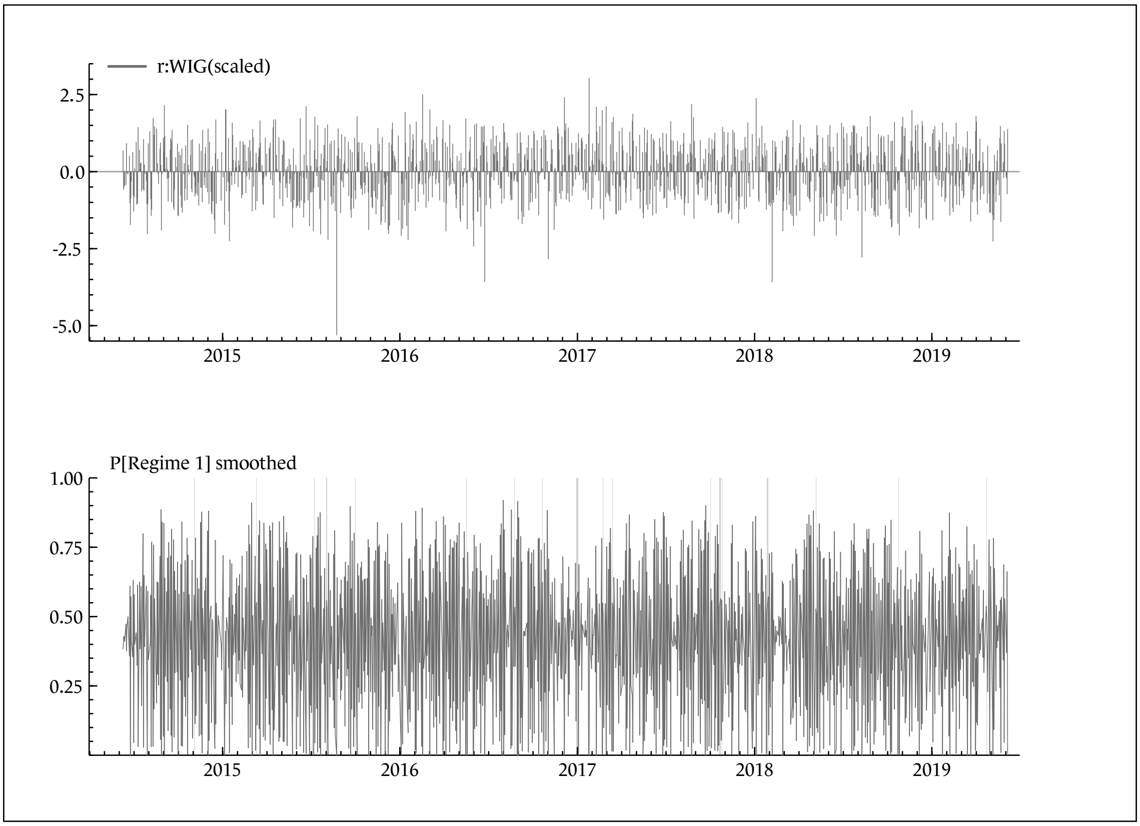
Source: own calculations.

Figure 2
Daily returns and regime 1 probabilities with sWIG80 regimes in 2014–2019



Source: own calculations.

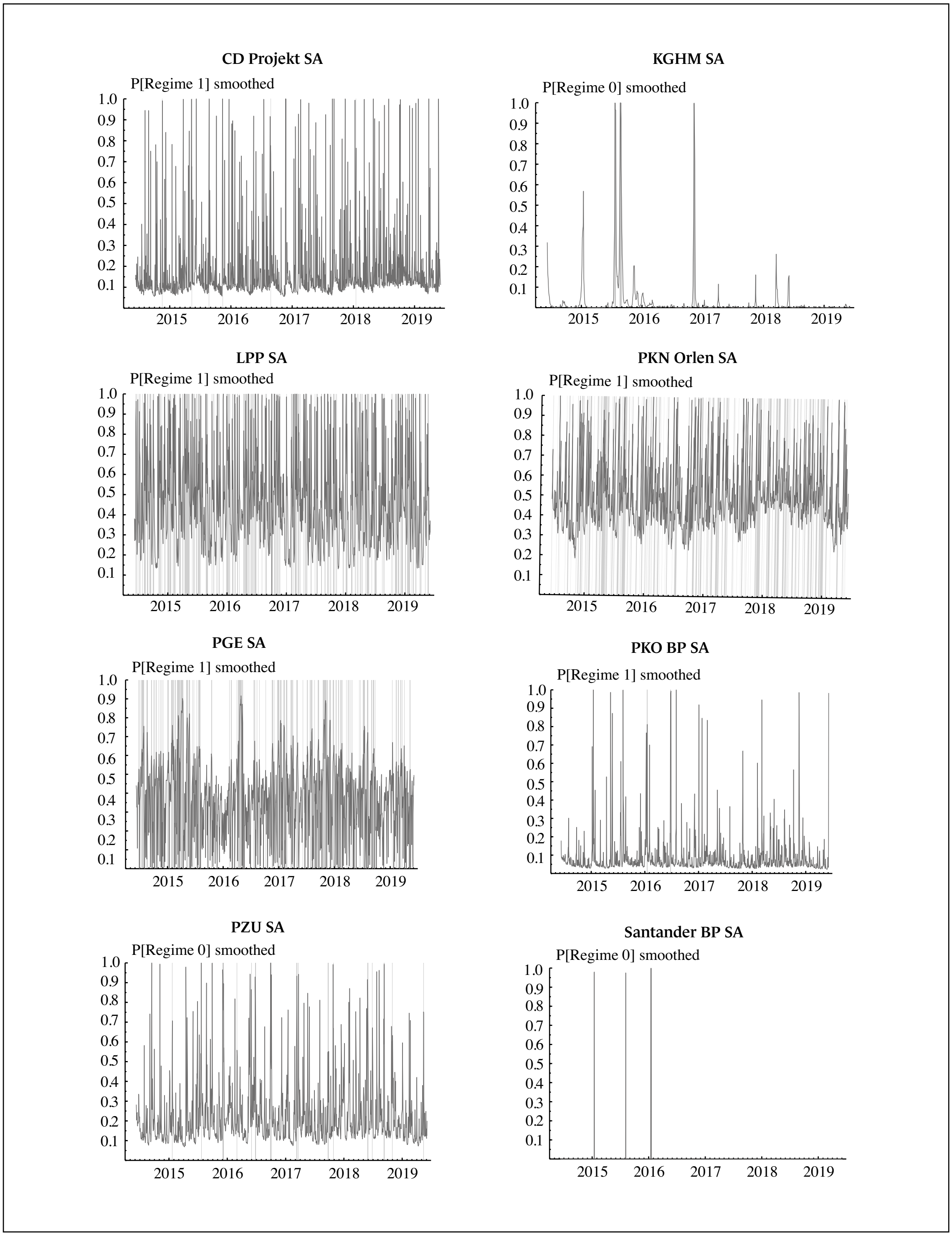
Figure 3
Daily returns and regime 1 probabilities with WIG regimes in 2014–2019



Source: own calculations.

Figure 4

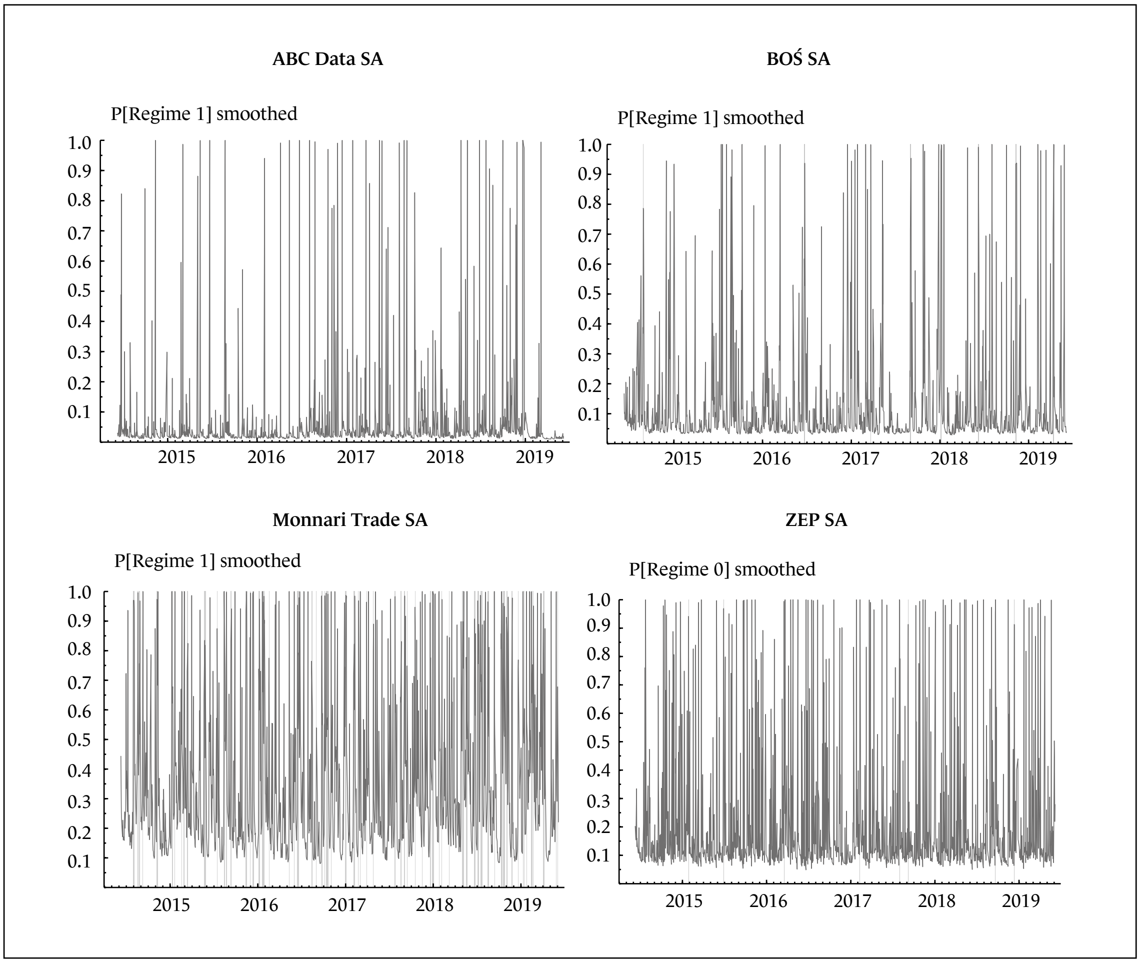
Regime 1 probabilities and regimes for eight companies listed on the WIG20



Source: own calculations.

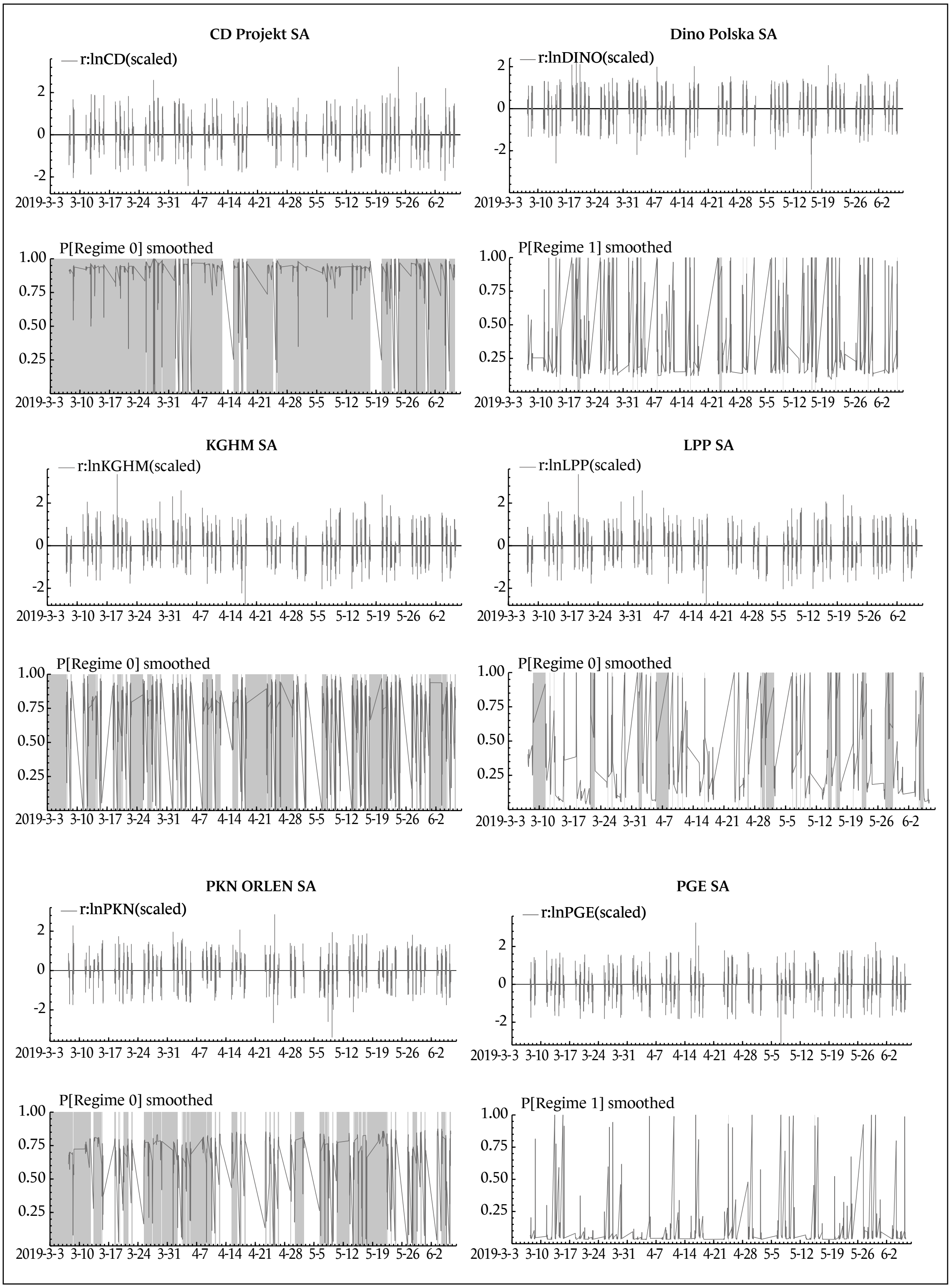
Figure 5

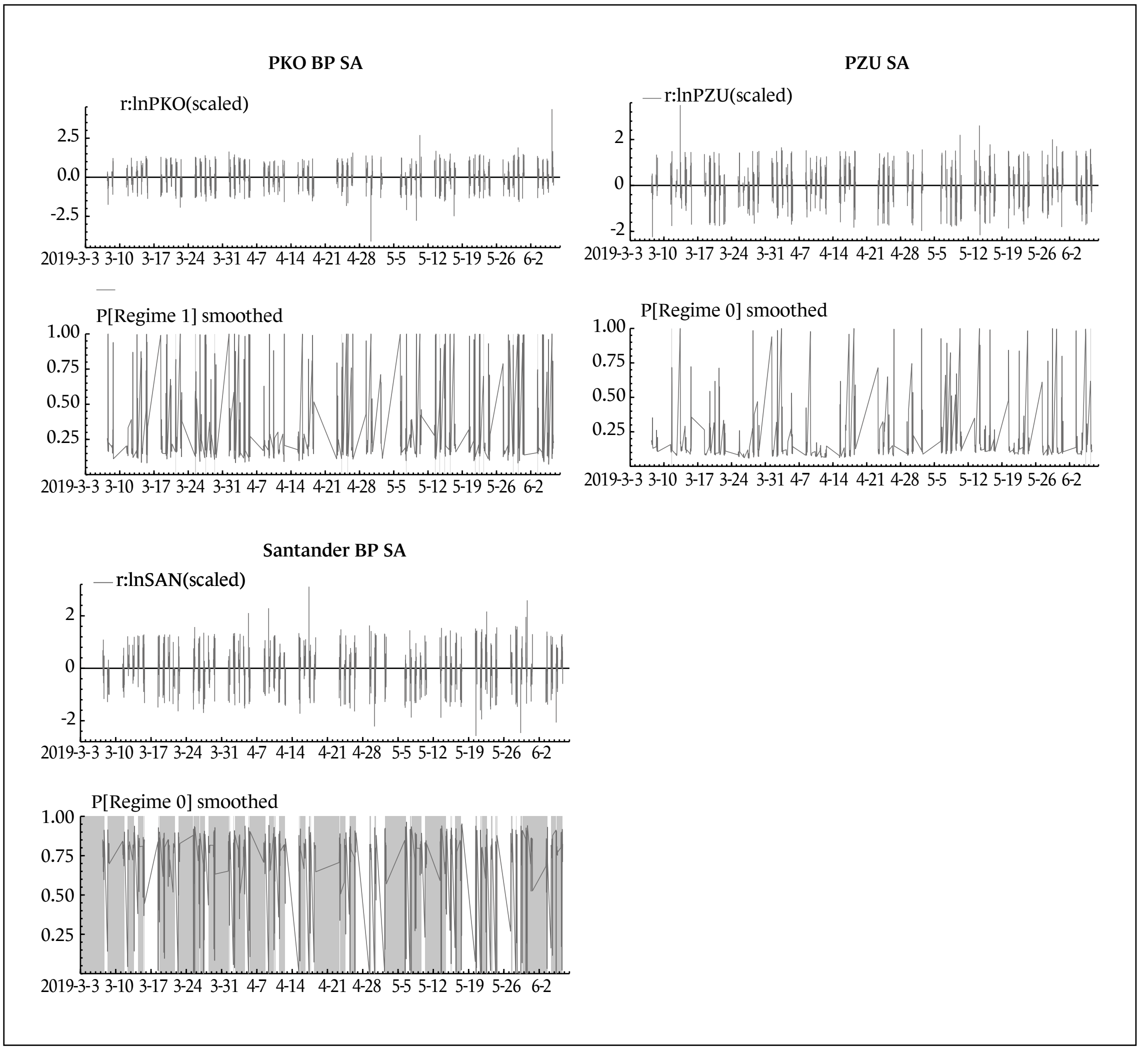
Regime 1 probabilities and regimes for four companies listed on the sWIG80



Source: own calculations.

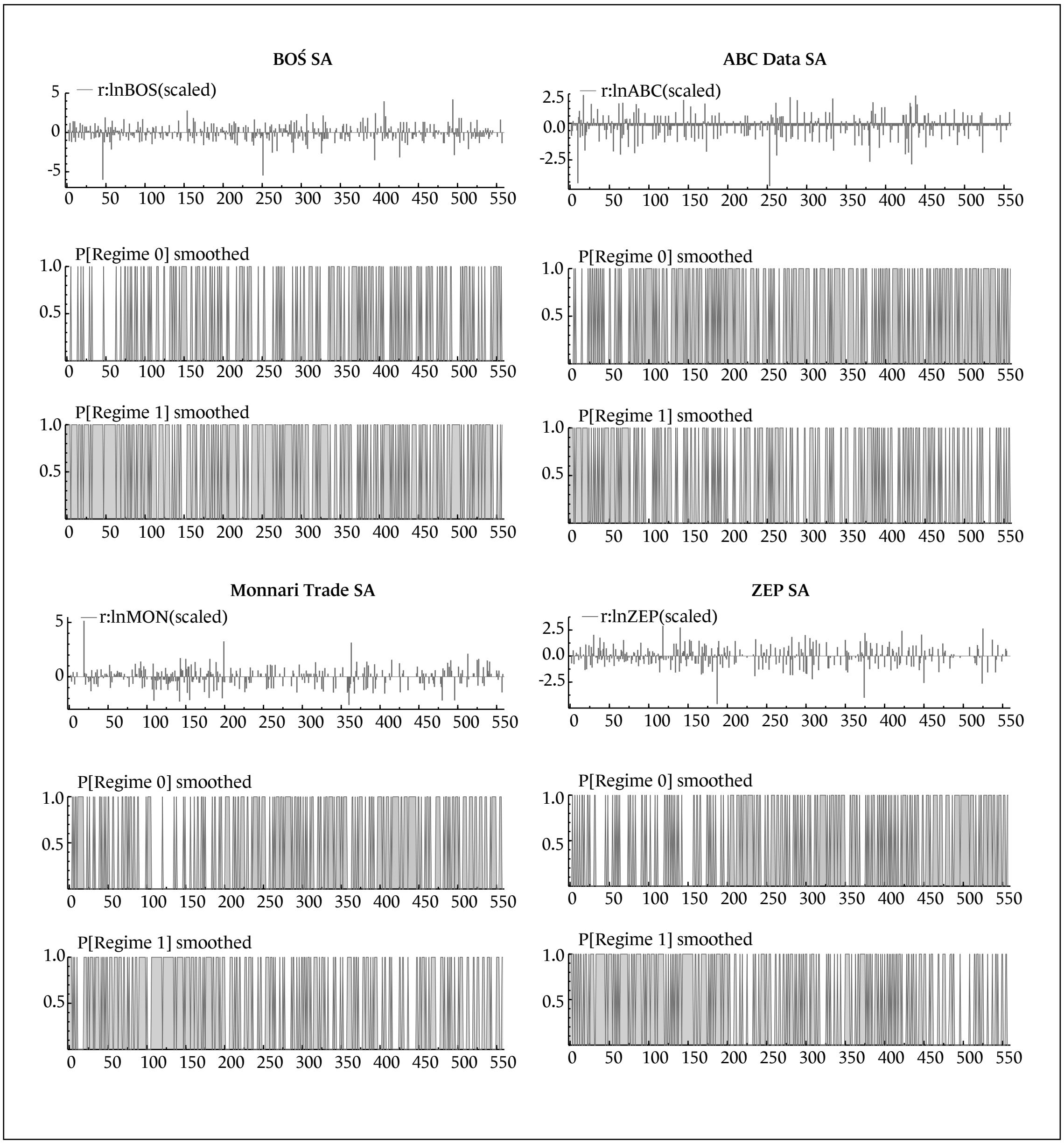
Figure 6
Intraday returns, regime probabilities and regimes for nine companies listed on the WIG20





Source: own calculations.

Figure 7
Hourly returns and regime probabilities with regimes for sWIG80 companies



Source: own calculations.