Majewski, S., & Mentel, U. (2022). Analysis of the properties of weather regressors for econometric modelling: Example of weather stations in Poland. *Journal of International Studies, 15*(2), 122-139. doi:10.14254/2071-8330.2022/15-2/9

Journal of International Studies

Scientific Papers

Analysis of the properties of weather regressors for econometric modelling: Example of weather stations in Poland

Sebastian Majewski
Institute of Economics and Finance,
University of Szczecin,
Poland
sebastian.majewski@usz.edu.pl
ORCID 0000-0003-3072-5718

Urszula Mentel
Department of Projects Management and Security Policy,
Rzeszow University of Technology,
Poland
u.mentel@prz.edu.pl
ORCID 0000-0003-2060-8980

Abstract. Many recent works indicate the existence of a significant relationship between weather factors such as pressure, humidity, windspeed, sum of falls or sunshine and rates of return for stocks quoted on stock exchange. A properly conducted econometric study requires a careful analysis of the properties of the factors that will be used in the econometric model to explain the development of the dependent variable. The aim of the research is to check if the weather factors could be used as econometric regressors by verifying their statistical propensities. The analysis was held on the weather stations located in eight cities in Poland: Poznan, Kolo, Plock, Warsaw, Wroclaw, Opole, Katowice and Rzeszow. These cities host registered offices of the biggest companies of the energy sector in Poland. The research methods were focused around basic statistics and normality tests of distributions of weather factors' (four types), as well as the autocorrelation of regressors.

Received: June, 2021
1st Revision: February, 2022
Accepted: June, 2022

DOI: 10.14254/2071-8330.2022/15-2/9

Keywords: weather, sustainability, energy sector stocks, statistics, econometrics.

JEL Classification: Q54, N7, C46, C55

1. INTRODUCTION

The modern economic science is not only the study of resource efficiency or profit maximization, but also the study of sustainable development and the balanced impact of both the economy on the environment and the environment on the economy (Tamasauskiene & Žičkienė, 2021). Two strands need to be considered here - sustainable development of economies, with the impact of human activity on the environment, and behavioural finance, covering the impact of the environment on the human behaviour and reflected in changes in prices or the value of transactions (Zysk, 2020). Scientists are increasingly looking for solutions to preserve the environment in the least processed state possible, accepting any impact of environmental factors (including the weather). Over the years, humans have tried various means, including mathematical description, to tame nature and use it to achieve their goals. The direct perception of the finite nature of resources (scientists' calculations show how much of a resource there is left) is making people think about ways of using renewable energy sources and not wasting those which cannot be renewed (Pach-Gurgul & Ulbrych, 2019).

This study assumes that the analysis of the properties of the regressors of econometric models describing for example rates of returns and trading volume allows for a correct assessment of the impact of external incentives on the formation of rates of return and trading volumes of companies in the energy sector listed on the Warsaw Stock Exchange. Only thorough verification of the regressors' properties allows for the most precise description of the explained process, accurate model estimation and avoidance of significant errors in the next steps. Therefore, we attempted to assess the properties of weather variables used for econometric modelling of basic parameters describing securities trading. Such an assessment, in the light of the requirements of the statistical and econometric methods used, allows for the selection of an appropriate path for further econometric modelling. This type of information can also give potential stock market investors an idea of the additional risks to which investments in energy companies in Poland are exposed. The last part of the article contains econometric models for one of the Polish stock exchange companies – Lotos. The estimated models are the example of implementing information about propensities of weather factors in modelling rates of return and trading volume.

2. LITERATURE REVIEW

Sustainable development became the most urgent project for international policy at the United Earth Summit in Rio in 1992 (Chichilnisky, 1997). The United Nations Agenda 21 describes a necessity of realizing policy by all activities satisfying of basic needs in developing countries. One of the first definition of sustainable development describes it as a development, which satisfies present needs without making any problems for future generations (Brundland, 1987). The discussion on sustainable development is often an exchange of emotionally charged statements rather than substantive arguments. Solow argued that the point of a substantive discussion on this topic is to carry out a valuation of resources in a way that does not disregard future interests and utility (Solow, 1992). A problem worth considering is that standard cost-benefit analysis does not take the future into account. Evaluating processes for the safe disposal of waste from a nuclear power plant or policies to prevent global warming are among the many easy examples to cite. The benefits of both the first and second actions may be felt decades or even a century from now, while the costs must be borne now. Such a discrepancy between the treatment of the present and the future makes it difficult to justify socially desirable investment decisions.

Much research on valuing the future of the present has been conducted in the form of scientific experiments (Lowenstein & Thaler, 1989; Cropper et al. 1994; Lowenstein & Elster, 1992). The experiments show that 'tomorrow' becomes increasingly important as time passes. A situation similar to observing events from the future through a curved lens. In this case, the relative weight given to two consecutive periods in the future is inversely proportional to their distance from today. The experimental approach is directly related to the latter pathway, namely behavioural economics and the influence of external factors on individuals' attitudes.

Many psychological studies support the fact that, depending on mood, individuals are more predisposed to pessimistic or optimistic expectations (Arkes et al., 1988; Etzioni, 1988; Romer, 2000). Therefore, individuals like investors and stock market players, should also be subject to subjective attitudes (e.g., mood, feelings, etc.) during making decisions process. Furthermore, weather conditions could affect people's mood and therefore among others sunny days are associated with positive perceptions of the world and information, whereas rainy or cloudy days are often equated with depressive mood and pessimism (Cunningham, 1979; Howarth & Hoffman, 1984). The psychological literature also demonstrates that people feel happier on sunny days, while the absence of sunshine has the opposite effect (Schwarz & Clore, 1983; Eagles, 1994). This is mainly due to the perception of bright colours and sunlight as irritants that influence and evoke positive feelings, while grey skies and darkness are associated with negative emotions. There is even a special method of sunlight treatment to offset depression, apathy and melancholy (McAndrew, 1993). Therefore, different weather factors can influence stock market players, as well as other people, on their decisions through psychological channels of mood and perception. This in turn may have an impact on stock returns, as investors are hypothetically more likely to buy stocks during sunny weather and are more likely to sell when the weather is bad.

Classical theories of economics and finance tend to assume that investors are fully rational and that sentiment has no impact on stock prices. However, some studies suggest that a systematic change in sentiment, associated with events seemingly unrelated to economic fundamentals, can have a significant and predictable impact on the prices of these instruments. A systematic change in investor sentiment is believed to be associated with events such as a change in the number of daylight hours (Kamstra et al., 2003), rainy days (Hirshleifer & Shumway, 2003), lunar cycles (Yuan et al., 2006), temperature (Cao & Wei, 2005) and the performance of a national sports team (Edmans et al., 2007). These can have economically significant effects on stock prices.

The conclusions drawn from studies are often the subject of scientific debate. Some of them are contested due to certain methodological limitations that do not warrant wider generalizations. In the critical literature on the subject one can find statements that:

- their results may be the result of data mining (Sullivan et al., 2001);
- some results documented in these studies may be sensitive to outliers (Pinegar, 2002);
- results are influenced by chance (Fama & French, 1998);
- evidence based on market data only indicates a relationship, not a causal relationship, between various events and stock prices.

In such situations, the explanation that, according to classical theories of economics and finance, other factors influence stock prices cannot be excluded. For example, Gerlach (Gerlach, 2007) showed that most weather and calendar anomalies disappear when contemporary macroeconomic news announcements are taken into account. He concluded that market reaction to macroeconomic news, rather than psychological factors, explains these ap-parent anomalies.

The controversy over apparent anomalies highlights the need for a more accurate assessment of the relationship between investor sentiment and share prices. Bloomfield R. and Anderson A. (Bloomfield & Anderson, 2010), investigating the relationship between mood and stock price determinants, found that everything but mood is invariant, so any change in investor decision-making must be due to the only factor that systematically changes, namely mood. Psychologists argue that the decisions we make can strongly depend on our current emotional states. In general, people in a good mood make more optimistic judgements and are more willing to take risks (Johnson & Tversky, 1983; Wright & Bower, 1992). Conversely, when in a bad mood we are more likely to be pessimistic and more cautious in our decision making. In particular, mood changes strongly influence the evaluation of abstract phenomena that are distant in time and about which the decision-maker has no concrete and precise information (Forgas, 1995).

The role of emotions in risk perception and decision making has been systematically developed by Loewenstein G.F. et al. (Loewenstein et al., 2001), who found that emotions influence every element of the decision-making process. People have been found to form their preferences according to their mood, even when the reason for good or bad mood is completely unrelated to the decision problem. Complex psychophysical reactions have been linked to, among other things, changes in weather conditions, making them responsible for different aspects of human behaviour and work performance (Lu & Chou, 2012). Kals W.S. (Kals, 1982) showed that about one-third of people are sensitive to weather conditions, so that their mental and physical health suffers. Other studies have found that people appear to be more satisfied with their lives on sunny days than on cloudy and rainy days (Lucey & Dowling, 2005). Howarth E. and Hoffman M.S. (Howarth & Hoffman, 1984) found that weather variables are significant predictors of changes in most of the ten mood parameters. According to their study, humidity was the most important predictor, optimism was significantly related to the number of hours of sun-shine, and aggressive feelings increase when the temperature drops too very low.

Psychologists indicate that weather has unexpected effects on psychological aspects of humans, one of which is seasonal affective disorder (Lee & Wang, 2011), which can be easily explained by seasonal fluctuations in returns (Kamstra et al., 2003). Other studies in this area have examined the relationship between seasonal changes in daylight hours and stock prices. Kamstra et al. (Kamstra et al., 2003) found a correlation between stock returns and daylight hours (Garet et al., 2005) and attributed this effect to lowered mood resulting from seasonal affective disorder, a condition caused by lower levels of sunshine. In a related study, Kamstra M.J. et al (Kamstra et al., 2000) examined the effect of disturbed sleep patterns caused by changes to and from daylight saving time and found significantly lower returns following daylight saving time changes in the US, UK, Canada and German stock markets. Shu H.C. (Shu, 2010) showed that pleasant weather creates a good mood, inducing investors to optimise the stock market and vice versa. Symeonidis L. et al. (Symeonidis et al., 2010) verified that sunny weather affects investors' moods, making them more optimistic and willing to take long positions, which in turn leads to higher returns. Investors under the influence of an optimistic or pessimistic psychological state overestimate or under-estimate their outlook on the future of the economy, so they buy or sell more shares. Because weather conditions can affect a person's behaviour and mood, investors in a good mood tend to be more optimistic about future prospects and show more willingness to invest. This in turn makes them overestimate the probability of success and underestimate the risk of their decision (Wright & Bower, 1992; Nofsinger, 2005).

In one of the early studies on the impact of mood, Saunders E.M. (Saunders, 1993) found that changes in mood due to changes in cloudiness levels could affect stock prices. He examined the relationship between cloudiness in New York City and the daily returns of a number of New York stock indexes. As a result, he found that changes in sentiment related to cloud cover levels affect stock prices. Hirshleifer D. and Shumway T. (Hirshleifer & Shumway, 2003) re-ported that the sunshine effect is not limited to New York City. They documented the relationship between cloudiness and stock prices in 18 of the 26 countries studied. The annual difference in returns between sunny and cloudy days indicated in their study was as high as 24.6 per cent in some markets, highlighting the economic importance of this effect. They recommended that investors use knowledge of sentiment caused not only by weather, but also by other types of conditions, in order to avoid sentiment-related errors in financial assessments and transactions. Similar findings come from the team of Bassi A., Colacito R. and Fulghieri P. (Bassi et al., 2013). They provided experimental evidence of the relationship between weather, mood and risky behaviour of subjects. The authors of this paper identified a risk tolerance transmission pathway through which weather affects investment decisions. Mood appears to be the transmission mechanism in this case, through which good weather favours risky behaviour. In particular, temperature and air pressure positively influence our buy-sell transactions. In addition, a negative relationship between cloudiness and willingness to buy was also discovered.

Later studies extended the analyses to include the relationship with stock prices of various other weather phenomena (such as temperature, precipitation, humidity, wind speed) and also the relationship across countries (Pardo & Valor, 2003; Cao & Wei, 2005; Chang et al., 2006; Dowling & Lucey, 2008). The results of these studies support the hypothesis that changes in mood caused by a range of weather events are associated with changes in stock prices.

3. METHODOLOGY

The data for the analysis are collected form the Institute of Meteorology and Water Management in Warsaw from 2015 to 2020 for eight chosen localizations such as Poznan, Kolo, Plock, Warsaw, Wroclaw, Opole, Katowice and Rzeszow. These localizations correspond to headquarters of biggest energy companies in Poland, quoted on the Warsaw Stock Exchange. Authors decided to analyse six weather factors influencing on rates of return of energy companies (Tarczynski et al., 2021). There were analysed following factors: air temperature, insolation, wind speed, atmospheric pressure, atmospheric humidity and rainfall.

Research was focused on the analysis of statistical properties of weather factors. Therefore, it uses statistical parameters and tests to describe as accurately as possible changes of weather factors' values. The research has three levels:

1. analysis of descriptive statistics
2. testing of distributions of weather factors' normality
3. testing of autocorrelation

The first step of the research was analysis based on tools of descriptive statistics. Descriptive analysis using simple parameters such as mean, median, mode, standard deviation or coefficients of kurtosis and skewness allows to determine which kind of theoretical distribution is similar to empirical data distribution.

The second step is very important especially for choosing the method of estimation of econometric models. Some models have restrictions to the possibility of using non-normal distribution variables in the estimation process (i.e., OLS - ordinary least square). Therefore, it is very important to know variables' distribution and possibility of their applying for a proper econometric model. The lack of such verification (normality of distribution) could result in obtaining significant errors and mistaken interpretation. Supporting investment decisions such kind of incorrect results causes much more serious consequences - the increase of risk and financial losses. During this step following test are used (Ghasemi & Zahediasl, 2012):

1. Doornik-Hansen test
2. Shapiro-Wilk test
3. Lilliefors test
4. Jarque-Bera test

The third step was focused on the autocorrelation process. The problem of autocorrelation in data could negatively influence on the model's parameters estimation. The existing of autocorrelation is contrary to the third assumption of Gauss-Markov theorem (random errors have to be uncorrelated) (Hill et al., 2018). The lack of fulfilment of this term may cause false results and incorrect interpretations but it also could indicate other methods could be used, which do not generate methodological problems.

4. EMPIRICAL RESULTS AND DISCUSSION

Air temperature is an important weather factor. This is a factor that, according to many, affects not only the possible behaviour of financial instruments, but also constitutes a classic base element in the construction of the so-called weather forward instruments [49]. This is because most of the weather futures contracts are based on temperature indices [50].

It should be emphasized that the analysis of the considered weather factor, as well as the other ones discussed, looks slightly different in the case of daily (daily) data and different in the case of monthly periods. The properties and trends observed in the two cases are often fundamentally different. Therefore, due to the nature of the analyses performed in the further part of this publication, only daily data are analysed.

When performing the preliminary analysis of descriptive statistics, a certain tendency should be noticed regarding the skewness of the distribution of the feature (Table 1). In general, a slight left-hand asymmetry can be observed in the cross-section of the temperature analysis for the main meteorological stations in Poland. Only in a few cases, the so-called skewness is positive. This is in line with the observations contained in the publications, either Preś J. [51] or Mentel G. [49]. If in this case we take into account the daily data, but for individual months, the asymmetry analysis has a slightly different character, as the left-hand distribution is visible in the winter months, and the positive asymmetry is visible in the summer.

Table 1

Values of selected parameters of temperature distribution for the main synoptic stations in Poland in °C in 2015-2020 based on daily data

	Mean	Median	Mode	Standard deviation	Skewness	Kurtosis
Poznań	10.4486	9.85	4.20	7.8832	0.0022	-0.7810
Koło	9.9683	9.40	0.00	7.9930	-0.0089	-0.8056
Płock	9.7625	9.40	0.00	7.9255	-0.0552	-0.7731
Warszawa	10.2638	9.80	14.90	8.2745	-0.0718	-0.7688
Wrocław	10.9975	10.70	5.20	7.7771	-0.0299	-0.8065
Opole	10.6186	10.40	5.00	7.9550	-0.0531	-0.7715
Katowice	9.8920	9.80	Multiple	7.9929	-0.1149	-0.6714
Rzeszów	9.9244	9.95	Multiple	8.3332	-0.1453	-0.7197

Source: Authors' results.

In the analysis of daily temperature data, the normality of the distribution should be excluded (Table 2). In the cross-section of several statistical tests, the indications are unambiguous. The tested property appears only when an analysis is performed across months for daily data.

Table 2

Tests of normality of temperature distributions for selected synoptic stations in Poland in 2015-2020 based on daily data

	Doornik-Hansen test	p-value	Shapiro-Wilk test	p-value	Lilliefors test	p-value	Jarque-Bera test	p-value
Poznań	75.3383	4.370×10^{-17}	0.9838	4.169×10^{-15}	0.0537	~=0.000	55.860	7.416×10^{-13}
Koło	81.1904	2.343×10^{-18}	0.9812	2.140×10^{-16}	0.0553	~=0.000	59.392	1.268×10^{-13}
Płock	76.3999	2.570×10^{-17}	0.9817	3.771×10^{-16}	0.0576	~=0.000	55.846	7.469×10^{-13}
Warszawa	77.4071	1.553×10^{-17}	0.9806	1.042×10^{-16}	0.0611	~=0.000	56.008	6.885×10^{-13}
Wrocław	82.2769	1.361×10^{-18}	0.9839	5.543×10^{-15}	0.0518	~=0.000	59.871	9.984×10^{-14}
Opole	75.8100	3.452×10^{-17}	0.9837	3.899×10^{-15}	0.0528	~=0.000	55.535	8.725×10^{-13}
Katowice	63.9353	1.308×10^{-14}	0.9832	2.095×10^{-15}	0.0559	~=0.000	46.141	9.562×10^{-11}
Rzeszów	81.2142	2.315×10^{-18}	0.9802	6.849×10^{-17}	0.0635	~=0.000	55.167	1.049×10^{-12}

Source: Authors' results.

The effect of data autocorrelation seems to be visible after analysing the figure below (Figure 1). The autocorrelation effect is shown here only for the cities of Katowice and Rzeszów, but this tendency is maintained for every other meteorological station under consideration. The statistics of the Ljung-Box test confirm the occurrence of the correlation phenomenon over time, but it fades out exponentially.

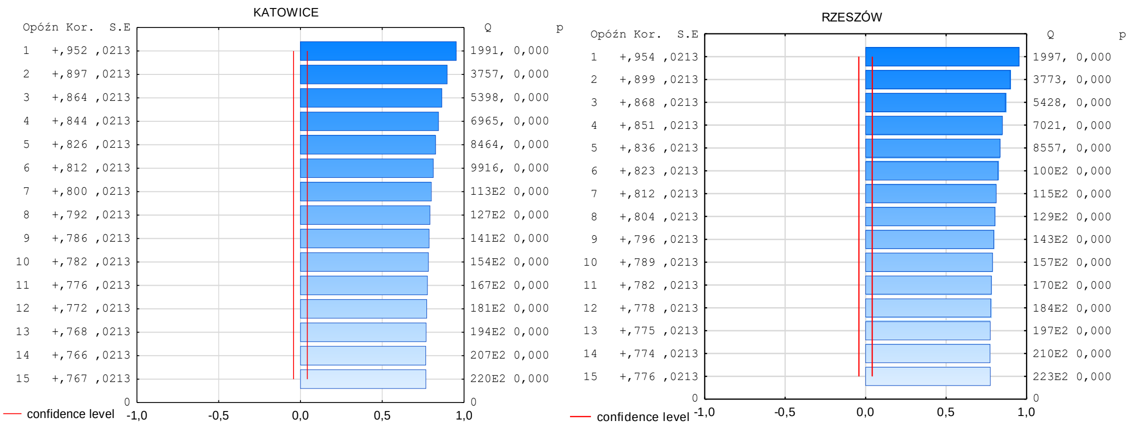

Figure 1. Autocorrelation function for the daily air temperature for the cities of Katowice and Rzeszów in 2015-2020

Source: Authors' results.

The nature of the phenomenon is slightly different in the case of the analogous analysis for the average monthly temperature values. Then, there is also a clear seasonality of data, also associated with warm and cold periods.

Another analysed element is the so-called insolation, which in this case is understood as the total time (in hours) during the day in which solar radiation falls on a specific place on the Earth's surface. The analysis of the basic characteristics of the distribution (Table 3) allows for the observation of relatively small asymmetries of various directions. The concentration measure values additionally indicate a significant flattening of the distribution (platokurticity).

Table 3

Values of selected parameters of insolation distribution for the main synoptic stations in Poland in hours in 2015-2020 based on daily data

	Mean	Median	Mode	Standard deviation	Skewness	Kurtosis
Poznań	8.5372	8.80	Multiple	4.0934	-0.1097	-0.9550
Koło	8.3746	8.80	13.40	3.7850	-0.2840	-0.9035
Płock	8.1338	8.30	10.40	3.9687	-0.1252	-0.9834
Warszawa	7.3302	7.15	10.10	4.0356	0.0868	-1.0071
Wrocław	9.0133	9.40	9.80	3.5337	-0.3003	-0.7340
Opole	8.6315	9.00	9.60	3.5932	-0.3266	-0.7133
Katowice	7.9721	8.20	Multiple	3.7566	-0.2291	-0.8814
Rzeszów	6.9069	6.90	Multiple	3.5881	-0.1651	-1.0093

Source: Authors' results.

When considering the nature of the distribution of the analysed feature, it should also be stated in this case that the lack of so-called normality. The evaluation of the phenomena in the cross-section of several statistical tests (Table 4) gives clear indications.

Table 4

Tests of normality of insolation distributions for selected synoptic stations in Poland in 2015-2020 based on daily data

	Doornik-Hansen test	p-value	Shapiro-Wilk test	p-value	Lilliefors test	p-value	Jarque-Bera test	p-value
Poznań	168.347	2.779×10^{-37}	0.9591	4.593×10^{-21}	0.0681	~=0.000	88.948	4.843×10^{-20}
Koło	190.071	5.332×10^{-42}	0.9479	1.685×10^{-23}	0.0755	~=0.000	104.396	2.142×10^{-23}
Płock	185.123	6.324×10^{-41}	0.9498	4.053×10^{-23}	0.0778	~=0.000	97.769	5.883×10^{-22}
Warszawa	223.108	3.569×10^{-49}	0.9468	6.160×10^{-24}	0.0834	~=0.000	101.778	7.928×10^{-23}
Wrocław	177.335	3.107×10^{-39}	0.9561	2.940×10^{-23}	0.0689	~=0.000	103.980	2.636×10^{-23}
Opole	181.093	4.744×10^{-40}	0.9549	2.508×10^{-23}	0.0803	~=0.000	104.353	2.188×10^{-23}
Katowice	201.330	1.913×10^{-44}	0.9501	4.433×10^{-24}	0.0786	~=0.000	108.611	2.603×10^{-24}
Rzeszów	42.896	4.843×10^{-10}	0.9465	8.169×10^{-11}	0.0924	~=0.000	24.293	5.306×10^{-06}

Source: Authors' results.

The nature of the autocorrelation phenomenon (Figure 2) is in line with the observations made when discussing the temperature factor. This also applies to the possible analysis of this phenomenon for daily data, but in the breakdown of individual months. Then there is a clear seasonality, which in a way is intuitive and also related to the seasons of the year. Of course, the observations made in this case also apply to the remaining meteorological stations under consideration, and not only to the two presented in the figure below.

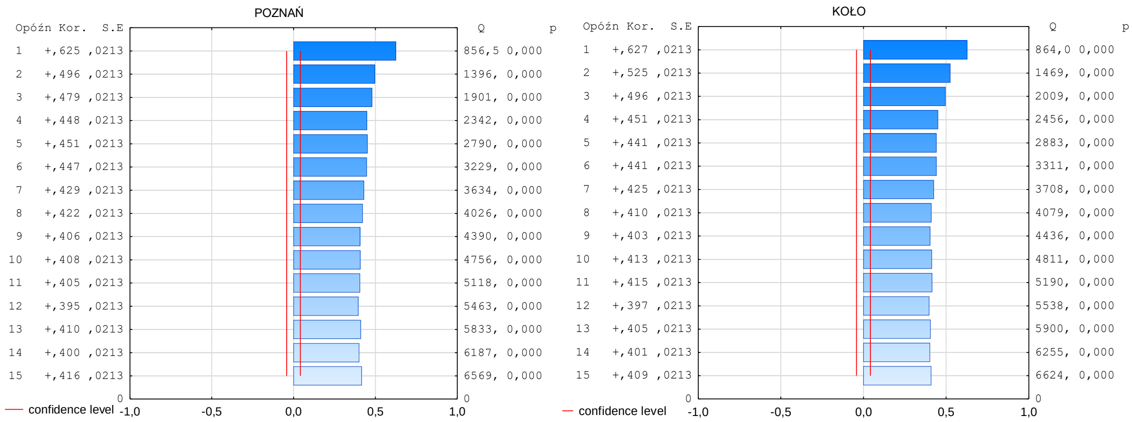

Figure 2. Autocorrelation function for the daily insolation for the cities of Poznań and Koło in 2015-2020

Source: Authors' results.

Wind speed is a weather factor that is equally important in the analysis of meteorological data. Already after the initial analysis, its character is different in relation to the factors considered earlier. It seems that the following graphic presentation (Figure 3) says a lot in this case. This is because a significant right-hand asymmetry of the distribution can be noticed, which completely rules out its normality. The Weibull distribution seems to be the most appropriate approximation in this case. In the case of wind speed, this type of distribution is mentioned in the literature as the most accurate (Wais, 2016).

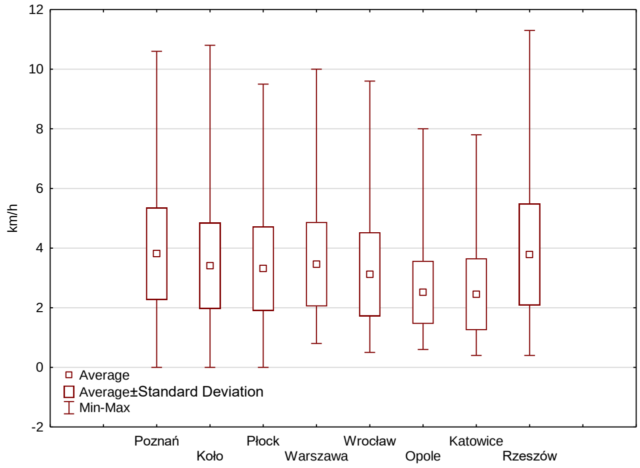

Figure 3. Box charts (frame-whiskers) for daily wind speeds [m / s] for selected synoptic stations in Poland in 2015-2020

Source: Authors' results.

After a statistical study consisting in matching the empirical distributions of the analysed factor to the log-normal, Gamma or Weibull distributions, the literature observations can be confirmed (Figure 4). The values of the statistics for the Cramer von Mises and Anderson-Darling tests only seem to confirm this belief.

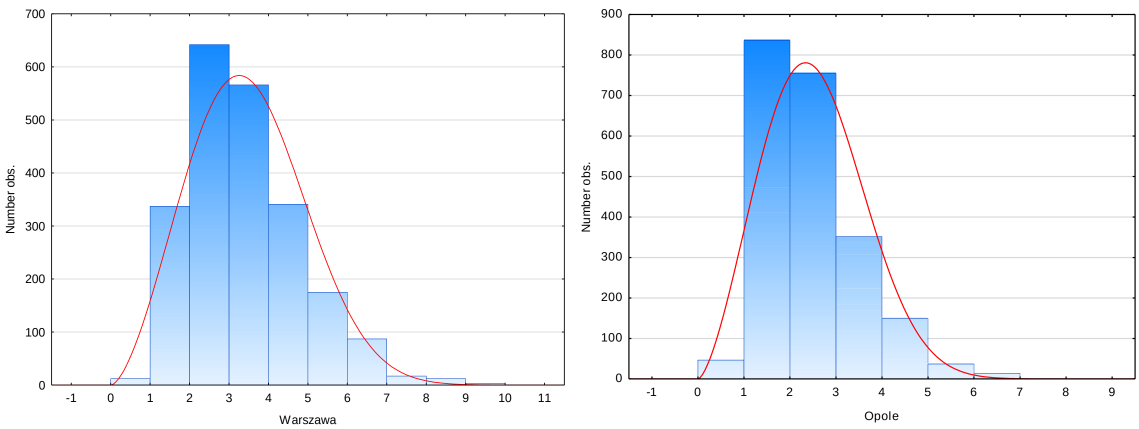

Figure 4. Distribution of the average daily wind speed in Warszawa and Opole in 2015-2020 with the matched Weibull distribution curve

Source: Authors' results.

The autocorrelation analysis, in the case of wind speed, shows a much faster fading out of the dependence effect over time, compared to the analogous analyses of the temperature factor or insolation (Figure 5).

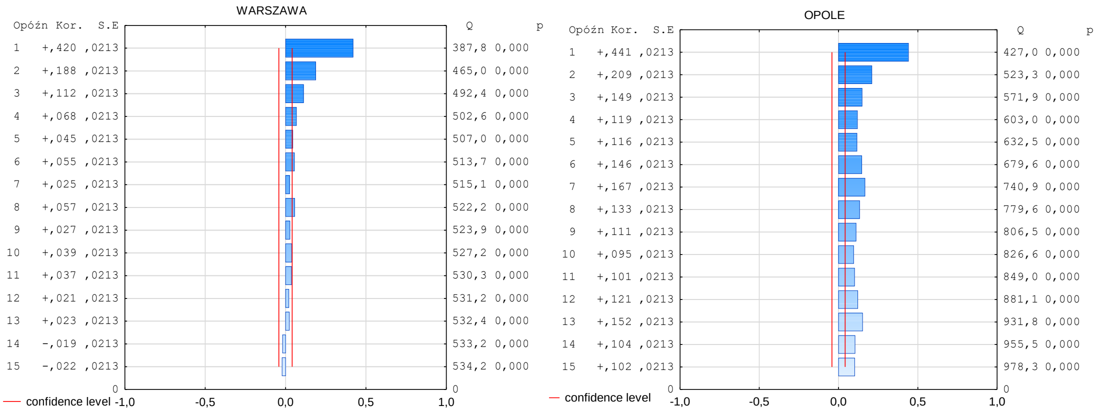

Figure 5. Distribution of the average daily wind speed in Warszawa and Opole in 2015-2020 with the matched Weibull distribution curve

Source: Authors' results.

Pressure is another factor that should be considered in the context of the possible impact on the mood of investors, and thus their investment decisions. Descriptive statistics of the mean daily sea-level pressure [hPa] for individual meteorological stations are presented in the table below (Table 5). Although the ranges of changes of this factor in the cross-section of weather stations are similar (the differences are not significant), a positive value of the concentration coefficient is noticeable, which proves a higher peak of the density function compared to the normal distribution (leptokurticity). In addition, along with the analysis of meteorological stations more and more distant from the sea, the average value of pressure increases, which is also natural. The same analysis shows a clear reduction in the typical range of volatility. Consequently, in the case of weather stations located higher up, the possible range of pressure changes is much smaller than in the case of coastal stations (located in lowland areas). The study of the variability of the phenomenon across months gives an additional observation about the increased dispersion in the cold months and the opposite tendency in the warm months.

Table 5

Values of selected parameters of the distribution of the mean daily pressure at the sea level [hPa] for the main synoptic stations in Poland in 2015-2020 based on daily data

	Mean	Median	Mode	Standard deviation	Skewness	Kurtosis
Poznań	1016.2790	1016.40	1014.60	8.8639	-0.2219	0.5364
Koło	1016.2938	1016.35	1013.50	8.7256	-0.1603	0.5040
Płock	1016.1628	1016.20	Multiple	8.7609	-0.1509	0.5351
Warszawa	1016.3990	1016.35	1016.80	8.5878	-0.0873	0.5254
Wrocław	1016.8226	1016.90	Multiple	8.5360	-0.1699	0.5477
Opole	1017.1591	1017.10	1015.80	8.3992	-0.1036	0.5091
Katowice	1017.4347	1017.30	1017.10	8.2408	-0.0574	0.5070
Rzeszów	1017.3563	1017.05	1015.60	8.0648	0.0414	0.4944

Source: Authors' results.

When analysing the values of the statistics of individual tests, a certain tendency can also be noticed. This is because, despite the general lack of normality of distributions, along with moving away from coastal areas, it is visible that the pressure distributions are getting closer to normal. The relatively lower values of kurtosis and the narrowing of the typical ranges of variability only confirm this observation. The Table 6 shows the analysis of the normality of the distribution of the feature.

Table 6

Tests of the normality of the distributions of the mean daily pressure at the sea level [hPa] for the main synoptic stations in Poland in 2015-2020 based on daily data

	Doornik-Hansen test	p-value	Shapiro-Wilk test	p-value	Lilliefors test	p-value	Jarque-Bera test	p-value
Poznań	30.283	2.655×10^{-07}	0.9945	2.867×10^{-07}	0.0321	~=0.000	43.858	2.994×10^{-10}
Koło	24.170	5.642×10^{-06}	0.9955	5.049×10^{-06}	0.0311	~=0.000	31.692	1.312×10^{-07}
Płock	25.955	2.312×10^{-06}	0.9953	2.413×10^{-06}	0.0327	~=0.000	33.686	4.844×10^{-08}
Warszawa	23.568	7.624510^{-06}	0.9962	2.392×10^{-05}	0.0265	~=0.000	27.623	1.004×10^{-06}
Wrocław	27.953	8.512×10^{-07}	0.9956	4.339×10^{-06}	0.0291	~=0.000	37.539	7.057×10^{-09}
Opole	22.767	1.138×10^{-05}	0.9963	3.816×10^{-05}	0.0251	~=0.000	27.234	1.219×10^{-06}
Katowice	21.628	2.012×10^{-05}	0.9964	4.308×10^{-05}	0.0239	~=0.000	24.306	5.274×10^{-06}
Rzeszów	20.500	3.536×10^{-05}	0.9962	2.728×10^{-05}	0.0249	~=0.000	22.604	1.235×10^{-05}

Source: Authors' results.

In this case, the adjustment of the distribution is ambiguous, because standard ones, such as GED or t-Student's, do not give good approximations. The first of the listed ones is slenderer than the normal distribution, but it is worse at outliers. The second, in turn, is better at the so-called thick tails, however, is more flattened compared to the N (0.1) distribution (Figure 6).

Possible attempts to adjust the timetables with the use of STATISTICA or SPSS packages give different results in the cross-section of weather stations. Therefore, it is difficult to indicate one or two dominant ones here.

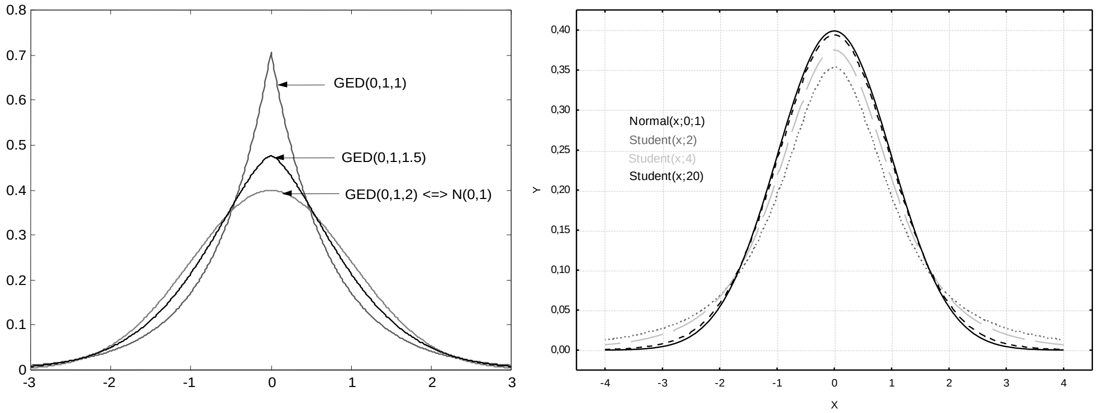

Figure 6. Graph of the GED and t-Student distribution density functions in relation to the normal distribution

Source: Authors' results.

The autocorrelation effect illustrated in the example below (Figure 7) shows that the effect fades quickly over time, regardless of the initial nature of the phenomenon.

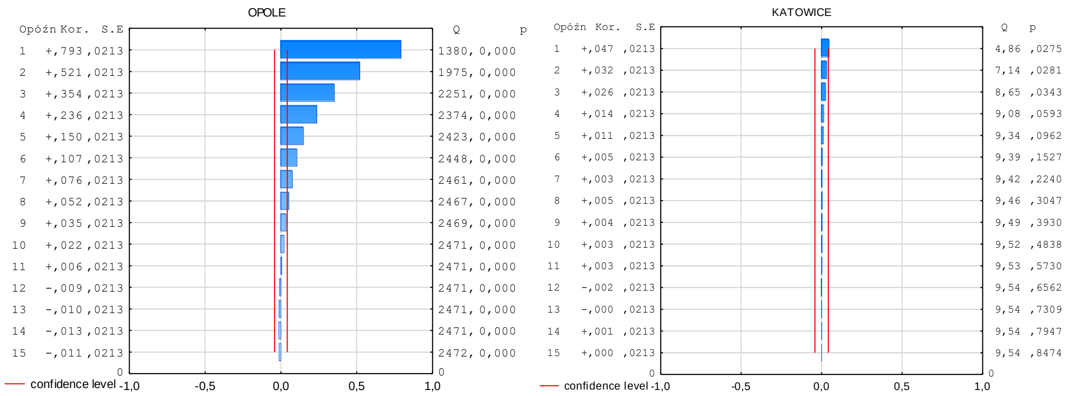

Figure 7. Autocorrelation function for the pressure at the sea level for the cities of Opole and Katowice in 2015-2020

Source: Authors' results.

Humidity is a factor that is also taken into account in research relating to the behavioural aspects of investment processes. In some cases, it is indicated as a significant variable. Therefore, it becomes reasonable to characterize the distribution of the feature, the more so that it is difficult to find such descriptions in the available literature. This fact is usually overlooked. Therefore, the analysis of the table below (table 7) may be a kind of novelty in this respect.

At first glance, there is a clear negative skewness, which proves the left-hand asymmetry of the distribution. The asymmetry is opposite to that observed for wind speed.

Table 7

Values of selected parameters of the distribution of the mean humidity for the main synoptic stations in Poland in 2015-2020 based on daily data

	Mean	Median	Mode	Standard deviation	Skewness	Kurtosis
Poznań	73.6394	75.40	81.90	14.5068	-0.3856	-0.7498
Koło	75.3205	76.55	71.90	13.2188	-0.3442	-0.7191
Płock	76.0751	77.10	Multiple	12.8401	-0.3845	-0.5904
Warszawa	73.8989	75.30	84.10	13.9913	-0.4324	-0.5226
Wrocław	73.2542	73.90	66.50	12.2771	-0.2431	-0.5739
Opole	74.1307	74.60	Multiple	12.2745	-0.2120	-0.5894
Katowice	75.2394	76.30	71.10	12.5327	-0.4168	-0.3624
Rzeszów	76.7223	77.90	76.90	12.6751	-0.4375	-0.3060

Source: Authors' results.

An analogous analysis across individual months is noteworthy, as shown in Figure 8. Although only the situation for three selected meteorological stations is shown, the behaviour of this factor is similar in the case of the others. Therefore, it seems that the months of the second half of the year are mainly responsible for the overall asymmetry in the distribution.

Therefore, the analysis of the possible normality of the distribution of the feature turns out to be unfounded in this case. Derogation from the so-called the Gaussian curve is clear, which is also confirmed by the values of kurtosis itself.

When referring to the autocorrelation phenomenon (Figure 9), it is necessary to emphasize the weak correlation in this case. The nature of the analysed variable differs significantly from the ones analysed so far.

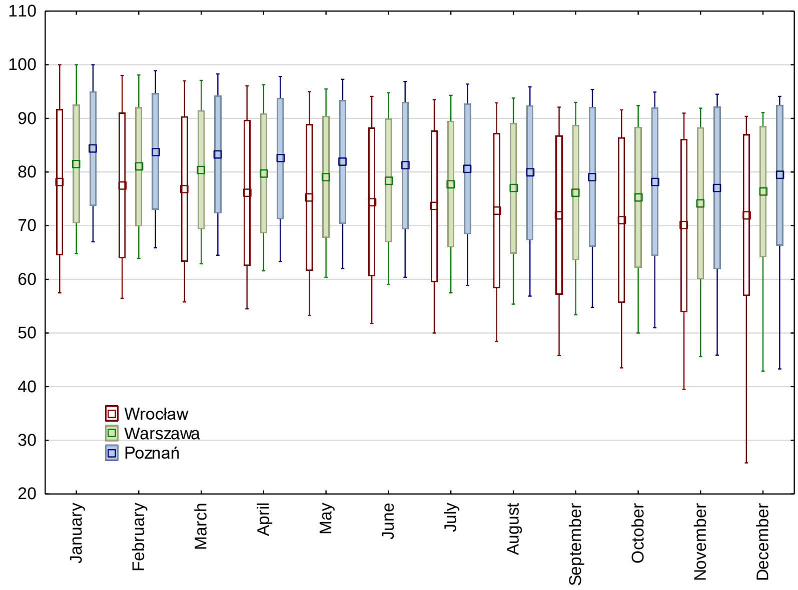

Figure 8. Box charts (box-whiskers) for daily values of relative humidity [%] for synoptic stations Wrocław, Warszawa, Poznań in 2015-2020

Source: Authors' results.

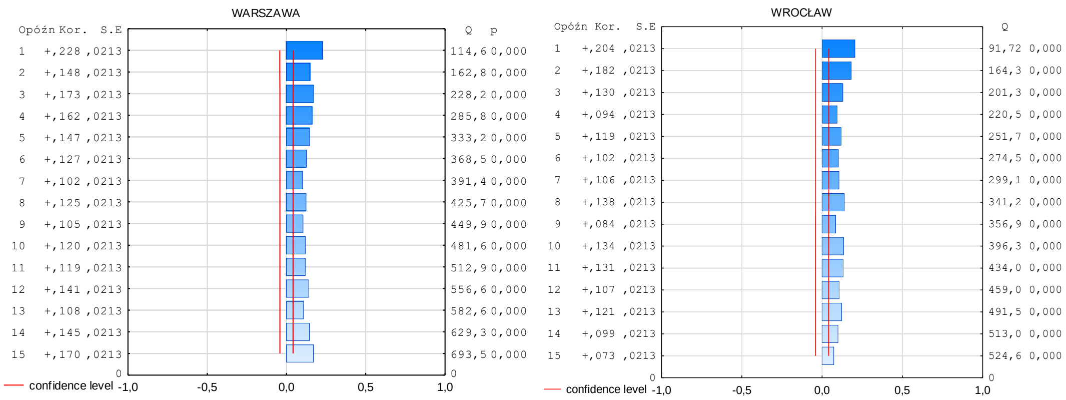

Figure 9. Autocorrelation function for the relative humidity for the cities of Warszawa and Wrocław in 2015-2020.

Source: Authors' results.

An interesting weather element in terms of the nature of the distribution is the amount of rainfall, understood in this case as the daily average total amount of rainfall without distinction to rainfall, snowfall or even hailstorms. It is an interesting variable as it is characterized by extreme right-hand asymmetry (Table 8). Median values generally oscillating between 0 and 1.5 confirm this tendency. The considered feature is additionally distinguished by a significant modal number. The repeatability of the dominant oscillates between 300 and 500 and its value is basically 0, which clearly indicates a large number of days without any precipitation. Significant skewness and significant concentration do not allow any of the commonly known distributions to fit. The analysis of the average daily precipitation values across individual months is slightly different. Then, in most cases, the fit of the distribution is close to the Weibull distribution.

Table 7

Values of selected parameters of the distribution of the rainfall for the main synoptic stations in Poland in 2015-2020 based on daily data

	Mean	Median	Mode	Standard deviation	Skewness	Kurtosis
Poznań	2.3784	0.70	0.00	4.3808	5.4685	56.6013
Koło	2.0890	0.40	0.00	4.2911	4.1432	23.5678
Płock	1.9192	0.30	0.00	3.9056	4.0794	23.5736
Warszawa	2.5067	0.70	0.00	4.6547	3.6019	17.3319
Wrocław	2.4800	0.60	0.00	5.3622	5.2496	41.2721
Opole	2.7783	0.80	0.00	5.2264	4.6010	34.1128
Katowice	3.1231	0.80	0.00	5.7485	4.4882	35.5134
Rzeszów	2.6267	0.80	0.00	4.5926	3.3748	15.2731

Source: Authors' results.

The phenomenon of dependence over time is in most cases negligible, or at least not long-term (Figure 10).

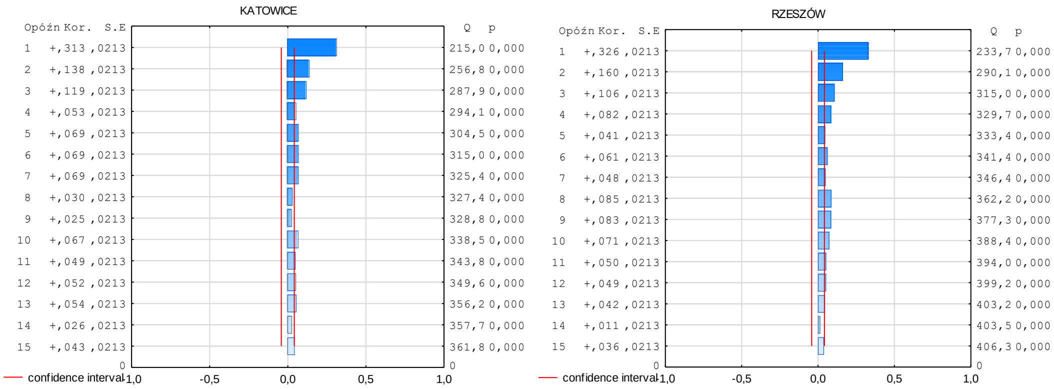

Figure 10. Autocorrelation function for the relative humidity for the cities of Katowice and Rzeszow in 2015-2020

Source: Authors' results.

Finally, when referring to the analysis of variance of the considered time series, it should be emphasized that statistical tests exclude the constancy of variance.

Such the analyses suggest to use dynamic econometric models to verify the assumption of influence of weather factors on the energy sector's company's stocks. The authors have chosen Lotos (petroleum company) to present the connections between stock exchange and weather. The table 8 presents results of econometric modelling using ARCH-type model.

Table 8

Results of econometric modelling of rates of return and trading volume using maximum likelihood function for Gdansk

Model describing trading volume for Lotos for location Gdansk Model: ARCH(1) [Bollerslev] (Normal)				
Conditional mean equation				
const	0.855468	0.274597	3.115	0.0018
Rainfall time	-0.0121887	0.004533	-2.689	0.0072
Daily average pressure	-0.0008156	0.000271	-3.012	0,0026
Equation of conditional variance				
omega	0,252411	0,0136342	18,51	$1.62 \cdot 10^{-76}$
alpha	0,193388	0,0354603	5,454	$4.93 \cdot 10^{-08}$

Model describing rates of return for Lotos for location Gdansk Model: ARCH(1) [Bollerslev] (Normal)				
Conditional mean equation				
const	-0.01564	0.00806	-1.940	0.0523
Daily average pressure	$1.5874 \cdot 10^{-05}$	$7.9427 \cdot 10^{-06}$	1.999	0.0457
Equation of conditional variance				
omega	0.000368	$2.25022 \cdot 10^{-05}$	16.33	$5.79 \cdot 10^{-60}$
alpha	0.285419	0.05144	5.549	$2.88 \cdot 10^{-08}$

Source: Authors' results.

The table contains information about the best approximation of stock exchange parameters influenced by weather factors. Both rate of return and trading volume indicates on the impact of daily pressure. The impact is negative for the trading volume – it means that if the value of the factor is growing up the values of trading volume is falling down. Similarly, the impact of rainfall time on the trading volume is also negative. Interesting fact is that the impact of pressure on rates of return is positive but near zero.

Because of the fact that the it is unclear what location should be assigned to the most active group of investors (origin location of company or the location of WSE) authors decided to analyse both cases. The Table 9 contains results for the location of Warsaw Stock Exchange (WSE).

Table 9

Results of econometric modelling of rates of return and trading volume using maximum likelihood function for Warsaw localization

Model describing rates of return for Lotos for location Warszawa Model: ARCH(1) [Bollerslev] (Normal)				
Conditional mean equation				
Daily average cloudiness	-0.000382	0.0002086	-1.832	0.0669
Daily average wind speed	0.000718	0.0002918	2.459	0.0139
Equation of conditional variance				
omega	0.000366	$2.27053 \cdot 10^{-05}$	16.13	$1.58 \cdot 10^{-58}$
alpha	0.285912	0.052316	5.465	$4.63 \cdot 10^{-08}$

Model describing trading volume for Lotos for location Warszawa Model: ARCH(1) [Bollerslev] (Normal)				
Conditional mean equation				
const	214264	26656.6	8.038	$9.14 \cdot 10^{-16}$
Daily sum of falls	-4688.12	1565,98	-2.994	0.0028
Daily average cloudiness	14004.0	4344.16	3.224	0.0013
Equation of conditional variance				
omega	$2.11217 \cdot 10^{+10}$	$3.67099 \cdot 10^{+09}$	5.754	$8.73 \cdot 10^{-09}$
alpha	1.20454	0.278314	4.328	$1.50 \cdot 10^{-05}$

Source: Authors' results.

The same analysis was made for the Warsaw localization – the location of the Warsaw Stock Exchange and a concentration of the largest number of stock market investors. The results are quite different. The biggest impact on the stock exchange parameters has: cloudiness and windspeed for rates of return and sum of falls and cloudiness for trading volume. The cloudiness has negative impact in case of rates of return and positive on trading volume. The windspeed has positive impact on rates of return and sum of falls has negative impact on trading volume. In presented cases it is justified to use ARCH-type models for estimation econometric parameters because of the fact that the residuals are well explained.

5. CONCLUSION

Authors of many scientific works use OLS method for the estimation of regression parameters without verifying fulfilment of assumptions. This work tries to identify real distribution of weather factors as regressor in econometric models and also problems of failure to meet the conditions.

The first analysed factor was air temperature. This variable characterizes relative symmetry, platokurticity and the distribution is not normal. The process of estimation of OLS parameters is complicated by autocorrelation process illustrated on the Figure 1. Therefore, it is justified to use another type of method not requiring uncorrelation of random errors such as Feasible Generalized Ordinary Least Squares (FGLS) method or Generalized Autoregressive Conditional Heteroskedasticity (ARCH-type) models. Such state of nature is quite normal because it is very rare situation when the weather is changing diametral during short-time period. Such situation is called then as extremal meteorological events.

Very similar situation concerns almost all results for daily insolation factor with exception of skewness coefficient, which in this case indicates on the moderate negative asymmetry. The persistence of sunshine-days in the sequence of a few days in the temperate climate zone is impossible but such phenomenon is more probable for the cloudiness (lack of insolation), so also in this case strong autocorrelations is normal.

The case of daily windspeed indicates on the negative asymmetry and leptokurtosis. The phenomenon of autocorrelation is limited to first three lags (days). It is connected to the fact that temperate zone characterizes quite high daily variability of windspeed.

Quite strange situation appears for daily pressure factor. The difference concerns to the pressure at the sea level for the cities of Opole and Katowice. Despite the fact that these two cities are distant from each other near 120 km, there is an autocorrelation for data from Opole (in the first 7 days) and there is no correlation for data from Katowice.

The statistics for humidity factor are similar to the results for daily insolation with the exception autocorrelation, which is not so strong as in the temperature case.

The last factor was rainfall. The results are quite different from the rest. The distribution of data is not normal but it characterizes positive strong asymmetry and strong leptokurtosis. The autocorrelation is distinct only for the first day.

The obtained results suggest to use other than OLS methods, which are not strongly restricted for non-normal distributed data. The authors recommend to use autoregressive models to estimate models using weather factors as independent variables (regressors) to obtain more precise results with low probability of making significant mistakes.

ACKNOWLEDGEMENT

The data is part of the research carried out by Ms Urszula Mentel in her doctoral dissertation entitled 'Weather conditions as a determinant of volatility in the stock market. Behavioral quantitative analysis' with supervision of prof. Sebastian Majewski.

FUNDINGS

The project was financed within the framework of the program of the Ministry of Science and Higher Education under the name "Regional Excellence Initiative" in years 2019-2022, project number 001/RID/2018/19, the amount of financing PLN 10,684,000.00.

REFERENCES

Arkes, H., Herren, L. T. & Isen, A. M. (1988). The role of potential loss in the influence of affect on risk-taking behavior. *Organizational Behavior and Human Decision Processes*, 42(2), 181-193. https://doi.org/10.1016/0749-5978(88)90011-8.

Bassi, A., Colacito, R., & Fulghieri, P. (2013). O Sole Mio: An Experimental Analysis of Weather and Risk Attitudes in Financial Decisions. *Review of Financial Studies*, 26(7), 1824-1852.

Bloomfield, R. & Anderson, A. (2010). Experimental finance. W H. K. Baker & J. R. Nofsinger, Behavioral Finance: Investors, Corporations, and Markets. NJ: Wiley.

Brundland, G. H. (1987). The U.N. World Commission on Environment and Development: Our Common Future. Oxford: Oxford University Press.

Cao, M. & Wei, J. (2005). Stock market returns: a note on temperature anomaly. *Journal of Banking and Finance*, 29, 1559–1573.

Chang, T., Nieh, C. C., Yang, M. J. & Yang, T. Y. (2006). Are stock market returns related to weather effects? Empirical evidence from Taiwan. *Physica A: Statistical Mechanics and its Applications*, 36, 343–354.

Chichilnisky, G. (1997). What is sustainable development?. *Land Economics*, 467-491.

Cropper, M. L., Aydede, S.K. & Portney, P. (1994). Preferences for Life Saving Programs: How the Public Discounts Time and Age. *Journal of Risk and Uncertainty*, 8. 243-265.

Cunningham, M. R. (1979). Weather, mood and helping behavior: Quasi-experiments with the sunshine Samaritan. *Journal of Personality and Social Psychology*, 37(11), 1947–1956.

Dowling, M., Lucey, B. M. (2008). Robust global mood influences in equity pricing. *Journal of Multinational Financial Management*, 18, 145–164.

Dutton, J. (2002). The Weather in Weather Risk. W B. Dischel, Climate Risk and the Weather Market. Risk Books.

Eagles, J. M. (1994). The relationship between mood and daily hours of sun light in rapid cycling bipolar illness. *Biological Psychiatry*, 36(6), 422-424. https://doi.org/10.1016/0006-3223(94)91216-5.

Edmans, A., Garcıa, D. & Norli, Ø. (2007). Sports sentiment and stock returns. *Journal of Finance*, 62, 1967–1998.

Etzioni, A. (1988). Normative-affective factors: Towards a new decision-making model. *Journal of Economic Psychology*, 9(2), 125-150.

Fama, E. F. & French, K. R. (1998). Taxes, Financing Decisions, and Firm Value. *Journal of Finance*, 53(3).

Forgas, J. P. (1995). Mood and judgment: The affect infusion model (AIM). *Psychological Bulletin*, 117(1), 39-66. https://doi.org/10.1037/0033-2909.117.1.39

Garret, I., Kamstra, M. J. & Kramer, L. A. (2005). Winter blues and time variation in the price of risk. *Journal of Empirical Finance*, 12, 291–316.

Gerlach, J. R. (2007). Macroeconomic news and stock market calendar and weather anomalies. *Journal of Financial Research*, 30, 283–300.

Ghasemi, A. & Zahediasl, S. (2012). Normality tests for statistical analysis: a guide for non-statisticians. *International journal of endocrinology and metabolism*, 10(2), 486.

Hill, R. C., Griffiths, W. E. & Lim, G. C. (2018). Principles of econometrics. John Wiley & Sons.

Hirshleifer, D. & Shumway, T. (2003). Good Day Sunshine: Stock Returns and the Weather. *The Journal of Finance*, 58(3), 1009-1032. https://doi.org/10.1111/1540-6261.00556

Howarth, E. & Hoffman, M. S. (1984). A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology*, 75(1), 15-23.

Johnson, E. J. & Tversky, A. (1983). Affect, generalization, and the perception of risk. *Journal of Personality and Social Psychology*, 45(1), 20-31. https://doi/10.1037/0022-3514.45.1.20

Kals, W. S. (1982). Your Health, Your Moods, and the Weather. New York: Doubleday.

Kamstra, M. J., Kramer, L. A. & Levi, M. D. (2000). Losing sleep at the market: the daylight saving anomaly. *American Economic Review*, 90, 1005–1011.

Kamstra, M. J., Kramer, L. A. & Levi, M. D. (2003). Winter blues: a SAD stock market cycle. *The American Economic Review*, 93(1), 324-343. https://doi/10.1257/000282803321455322

Lee, Y. M. & Wang, K. M. (2011). The effectiveness of the sunshine effect in Taiwan's stock market before and after the 1997 financial crisis. *Economic Modelling*, 28(1-2), 710-727.

Leroy, A. (2004). Design and Valuation of Wind Derivatives. Bruxelles: Universite Libre de Bruxelles.

Loewenstein, G. F., Weber, E. U., Hsee, C. K. & Welch, N. (2001). Risk as feelings. *Psychological Bulletin*, 127(2), 267–286. https://doi.org/10.1037/0033-2909.127.2.267

Lowenstein, G. & Elster, J. (eds.) (1992). Choice Over Time. New York: Russell Sage Foundation.

Lowenstein, G. & Thaler., R. (1989). Intertemporal Choice. *Journal of Economic Perspectives*, 3 (4), 181-93.

Lu, J. & Chou, R. K. (2012). Does the weather have impacts on returns and trading activities in order-driven stock markets? Evidence from China. *Journal of Empirical Finance*, 19(1), 79-93.

Lucey, B. M. & Dowling, M. (2005). The role of feeling in investor decision-making. *Journal of Economic Surveys*, 19(2), 211-238.

Majewska, A. (2013). Instrumenty pochodne jako narzędzia wspomagające zarządzanie ryzykiem w przedsiębiorstwie. Szczecin: Volumina.pl.

McAndrew, F. T. (1993). Environmental Psychology. A Division of International Thompson Publishing Inc, Brooks/Cole.

Mentel, G. (2017). Wartość zagrożona jako instrument zarządzania ryzykiem pogodowym. Rzeszów: Oficyna Wydawnicza Politechniki Rzeszowskiej.

Nofsinger, J. R. (2005). The psychology of investing (wyd. Second Edition). Pearson Education Hall.

Pach-GurgulA., & UlbrychM. (2019). Progress of the V4 Countries towards the EU's Energy and Climate Targets in the Context of Energy Security Improvement. *Entrepreneurial Business and Economics Review, 7*(2). https://doi.org/10.15678/EBER.2019.070210

Pardo, A., Valor, E. (2003). Spanish stock returns: where is the weather effect?. *European Financial Management*, 9, 117–126.

Pinegar, J. M. (2002). Losing sleep at the market: comment. *American Economic Review*, 92, 1251–1256.

Preś, J. (2007). Zarządzanie ryzykiem pogodowym. Warszawa: Wychwnictwa Fachowe CeDeWu.

Romer, P. (2000). Thinking and Feeling. *American Economic review*, 90(2), 439-443.

Saunders, E. M. (1993). Stock prices and the Wall Street weather. *American Economic Review*, 83, 1337–1345.

Schwarz, N. & Clore, G. L. (1983). Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. *Journal of Personality and Social Psychology*, 45(3), 513-523. https://doi.org/10.1037/0022-3514.45.3.513.

Shu, H. C. (2010). Investor mood and financial markets. *Journal of Economic Behaviour & Organization*, 76(2), 267-282. https://doi.org/10.1016/j.jebo.2010.06.004

Solow, R. (1992). An almost practical step toward sustainability; an invited lecture on the occasion of the Fourtieth Anniversary of Resources for the Future (No. AV 333.716 no. 13). Resources for the Future, Washington, DC (EUA).

Sullivan, R., Timmerman, A. & White, H. (2001). Dangers of data mining: the case of calendar effects in stock returns. *Journal of Econometrics*, 105, 249–286.

Symeonidis, L., Daskalakis, G. & Markellos, R. N. (2010). Does the weather affect stock market volatility? *Finance Research Letters*, 7(4), 214-223. https://doi.org/10.1016/j.frl.2010.05.004

TamasauskieneZ., & ŽičkienėS. (2021). An investigation of the nexus between globalisation dimensions and income inequality. *Entrepreneurial Business and Economics Review, 9*(2), 39-53. https://doi.org/10.15678/EBER.2021.090203

Tarczyński, W., Majewski, S., Tarczyńska-Łuniewska, M., Majewska, A. & Mentel, G. (2021). The Impact of Weather Factors on Quotations of Energy Sector Companies on Warsaw Stock Exchange. *Energies*, 14(6), 1536.

Wais, P. (2016). Two and tree-parameter Weibull distribution in aivailable wind power analysis. *Renewable Energy*, 103, 15-29. https://doi.org/10.1016/j.renene.2016.10.041

Wright, W. F. & Bower, G. H. (1992). Mood effects on subjective probability assessment. *Organizational Behaviour and Human Decision Processes*, 52(2), 276–291. https://doi.org/10.1016/0749-5978(92)90039-A

Yuan, K., Zheng, L. & Zhu, Q. (2006). Are investors moonstruck? Lunar phases and stock returns. *Journal of Empirical Finance*, 13, 1-23.

Zysk, W. (2020). Fair trade phenomenon and its evolution in Visegrad countries. *International Entrepreneurship Review, 6*(4), 81-98. https://doi.org/10.15678/IER.2020.0604.06