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THE EFFECTS OF BANKRUPTCY ON THE PREDICTABILITY OF PRICE FORMATION PROCESSES ON WARSAW'S STOCK MARKET

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Abstract

In this study we investigate how bankruptcy affects the market behaviour of prices of stocks on Warsaw's Stock Exchange. As the behaviour of prices can be seen in a myriad of ways, we investigate a particular aspect of this behaviour, namely the predictability of these price formation processes. We approximate their predictability as the structural complexity of logarithmic returns. This method of analysing predictability of price formation processes using information theory follows closely the mathematical definition of predictability, and is equal to the degree to which redundancy is present in the time series describing stock returns. We use Shannon's entropy rate (approximating Kolmogorov-Sinai entropy) to measure this redundancy, and estimate it using the Lempel-Ziv algorithm, computing it with a running window approach over the entire price history of 50 companies listed on the Warsaw market which have gone bankrupt in the last few years. This enables us not only to compare the differences between predictability of price formation processes before and after their filing for bankruptcy, but also to compare the changes in predictability over time, as well as divided into different categories of companies and bankruptcies. There exists a large body of research analysing the efficiency of the whole market and the predictability of price changes en large, but only a few detailed studies analysing the influence of external stimuli on the efficiency of price formation processes. This study fills this gap in the knowledge of financial markets, and their response to extreme external events.

JEL classification: G14, G33
Keywords: predictability, bankruptcy, complexity

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Introduction

The predictability of human actions is one of the most pressing questions in the social sciences as a whole (Song, Qu, Blumm & Barabási, 2010). In the particular case of economics these inquiries naturally follow in the direction of the predictability of prices (or their changes), and in finance this particularly means the predictability of stock returns. These returns are produced by complex adaptive social systems comprising large numbers of market participants (Rosser, 2008). The behaviour of these cannot be directly observed, and can only be analysed stochastically, in relation to the emergent laws that may appear from these complex interactions. This leads to a transdisciplinary approach to economic studies using methods based on statistical physics (econophysics). In fact one could say that, in so far as the emergence of prices is concerned, economics is a pure subject within statistical mechanics (Mantegna & Stanley, 2000). An approach based on fluid mechanics and information theory can be employed to estimate the predictability of price formation processes (this follows closely the mathematical definition of predictability), and in the case of financial research, potentially to study the relationship between predictability and profitability, which is as yet an unresolved problem (Fiedor, 2014a). There have been studies looking into the model free predictability measures operating on financial data, studying the structural complexity of time series describing logarithmic returns for various financial instruments. A few studies have also looked into the relationship between the predictability of the price formation processes and the profitability of various trading algorithms operating on these processes, as well as on finding phenomenological rules guiding this relationship and describing the possible approach to using the underlying structural complexity of the financial returns (Fiedor 2014a, 2014b). In this study we follow our earlier study, which looked into the effects of negative events outside the market itself on the predictability of the price formation processes which the events relate to (Fiedor & Hołda, 2014). We have looked at a small sample of companies which have undergone bankruptcy and found little evidence of the possibility of predicting bankruptcy through analysing the price formation processes. In this study we enhance this study in multiple ways. First, we employ a larger sample of 50 stocks traded on the Warsaw Stock Exchange, which filed for bankruptcy in the last few years (some are discarded in the analysis due to very short time series). Second, we look at the changes in predictability of the price formation processes both around the date of filing for bankruptcy, as well as around the date of the actual court order. Third, we analyse the studied effects with regards to the economic sector in which the company operates, the kind of bankruptcy, the market on which the stock is traded (New Connect & GPW), as well as the kind of accounting standards the company employs (IFRS & Polish law).

This paper is organised as follows. In the next section we present the definition and estimators of the predictability of price formation processes. In the following section we describe the used data and the obtained results, which are then discussed. The paper ends with brief concluding remarks.

Measures of predictability

In this section we describe the ways in which we measure the predictability of price formation processes. Predictability is rarely formally defined in economic studies. In mathematics, predictability is understood as the degree to which it is possible to know the next state of the system given its history (Capasso & Bakstein, 2012). There are two approaches to measuring predictability. The first approach consists in measuring errors of a fixed model (or a group of models) locally or globally, and deriving the predictability of a process on the basis of the distribution of the mentioned errors. This approach has very strong assumptions about the underlying generating process, and rests on the knowledge of how the error reacts when these assumptions hold or fail. The second (model-free) approach relaxes these restrictions, as it measures the predictability of a process based on redundancy found in its history (Garland, James & Bradley, 2014). Due to these restrictions, we use the second approach. As will presently become apparent, this approach also has a very direct connection with the mentioned definition of predictability.

To estimate the redundancy of an arbitrary process one has to know either the Kolmogorov-Sinai entropy of the process, or the values of all positive Lyaponov exponents of the process. The technical presentation of these is not necessary in this study, due to the above mentioned direct connotation between the used measure and the definition of predictability, nonetheless technically we will be approximating the Kolmogorov-Sinai entropy (Sinai, 1959). Finding all positive Lyapunov exponents would be equivalent, yet is practically impossible for financial data, as these exponents tend not to have finite values.

We measure predictability using tools from information theory (Cover & Thomas, 1991), particularly using the concept of entropy (in the sense of information theory, not thermodynamics). The predictability of a time series (stochastic dynamic process) can be estimated using Shannon's entropy rate. Entropy rate based on the notion of entropy, which measures the amount of uncertainty in a random variable *X*:

$$I(X) = -\sum_i p(x_i)\log_2 p(x_i), \tag{1}$$

summed over all possible outcomes x_i with their respective probabilities of $p(x_i)$.

The entropy rate generalises the notion of entropy for sequences of dependent random variables. Formally, for a stationary stochastic process $X = \{X_i\}$ the entropy rate is defined as:

$$H(X) = \lim_{n\to\infty}\frac{1}{n} I(X_1, X_2, ..., X_n), \tag{2}$$

$$H(X) = \lim_{n\to\infty} I(X_n \mid X_1, X_2, ..., X_{n-1}), \tag{3}$$

where (2) holds for all stochastic processes, but (3) requires stationarity of the process (Shannon, 1948). In particular, the right side can be directly equated with the mentioned mathematical definition of predictability. It can be interpreted so that the entropy rate measures the uncertainty in a quantity at time n knowing the complete history up to that point.

Estimation of the entropy rate is not a trivial problem, but these methods are relevant to many problems, not only in economics, but also in physics, biology etc. Methods of entropy estimation can be divided into two separate groups (Gao, Kontoyiannis & Bienenstock, 2006). The first group consists of maximum likelihood estimators (plug-in estimators), which study the empirical distribution of all words of a given length. This approach has exponentially increasing requirements for the sample size for higher word lengths, and also creates problems with bias. These estimators are not practical for analysing economic data. The second group consists of estimators based on data compression algorithms, most notably Lempel-Ziv (Ziv & Lempel, 1977) and Context Tree Weighting (Willems, Shtarkov & Tjalkens, 1995) algorithms. Both methods are precise even for a limited sample, and are thus better for analysing with mid- and long-term relationships in the analysed data. In our study we use Lempel-Ziv algorithm to estimate entropy rate, and, ultimately, predictability.

A number of estimators of entropy rate have been created based on the Lempel-Ziv estimator. In this study we use the estimator created by Kontoyiannis (1998). It is widely used, and its statistical properties are better than most similar estimators.

Formally, the mentioned estimator is defined as:

$$\hat{H}_{lz} = \frac{n\log_2 n}{\sum_i \Lambda_i}, \tag{4}$$

where *n* denotes the length of the studied time series, and Λ_i denotes the length of the shortest substring starting from time *i* that has not yet been observed prior to time *i*. It has been shown that for stationary ergodic processes, $\hat{H}_{lz}$ converges to the entropy rate $H(X)$ almost surely as *n* approaches infinity. For the purpose of this study we have implemented this estimator using C++. For detailed testing of this implementation see the study by Fiedor (2014a).

Obviously, we need concrete time series to feed into these estimators. As time series describing prices create issues with stationarity, we analyse time series containing logarithmic returns. If the most recent price of the studied financial instrument occurring on time *t* during the studied period by $p(t)$. Then for each stock the logarithmic returns are sampled:

$$\rho_t = \ln p(t) - \ln p(t-1), \tag{5}$$

For the purposes of the information-theoretic analysis we need to have discrete time series by binning the values into Ω distinct states. The discrete logarithmic returns r_t take values from an alphabet with cardinality Ω:

$$r_t \in \{1, ..., \Omega\}, \tag{6}$$

In our analysis we choose Ω=4, thus dividing the returns into quartiles. For the explanation of this choice and the discretisation step in general please see Refs. (Fiedor, 2014a, 2014b).

To complete the investigation we also calculate a less direct measure of predictability, which does not correspond directly to the presented definition, but is indirectly connected as the calculation involves the Lempel-Ziv estimator mentioned above. It is also a more practical measure, which takes into account the actual ability to predict the next price change given the history of some specified length, by trying to maximise the entropy rate at each step. Intuitively, this means predicting that the price formation process obeys the Efficient-Market Hypothesis at every point. This measure, and the related principle, are slightly paradoxical, as they appear to predict employing the apparent lack of predictability. Nonetheless, this measure can easily be interpreted as a practical measure of the predictive power of the related principle, as it is the percentage of times the principle correctly predicts the next price move.

The Maximum Entropy Production Principle (MEPP) has been proposed to deal with general theoretical issues of thermodynamics and statistical physics. This principle states that a non-equilibrium system develops so as to maximise its entropy production under present constraints. It has found applications not only in physics, but also biology and other fields (Martyushev & Seleznev, 2006).

If we understand entropy production as the Shannon's entropy rate, which is natural, then we can study time series describing logarithmic returns in a window of length μ ($\{r_{t-\mu},\ldots,r_t\}$). Under the principle of maximum entropy production we would state that the next price change r_{t+1} will be assigned the state which maximises Shannon's entropy rate, that is $H(\{r_{t-\mu},\ldots,r_{t+1}\})$. This approach predicts the price with the accuracy specified in the discretisation step, differentiating among Ω different levels. If $\alpha,\beta\in\{1,\ldots,\Omega\}$, the principle of maximum entropy production for stock returns can be written as:

$$\Psi = P(r_{t+1}=\alpha \mid \forall_{\beta\neq\alpha} H(\{r_{t=\mu},\ldots,r_t,\alpha\}) > \\ > H(\{r_{t=\mu},\ldots,r_t,\beta\}) = 1, \tag{7}$$

Theoretically this principle gives 100% accuracy, but financial markets are highly complex adaptive systems with many (known and unknown) constraints, thus in practice $\Psi\in(0,1)$, and is the practical measure of predictability mentioned above. Practically it is estimated by going through the time series with a running window approach of given length, and finding the percentage of times this principle correctly guesses the next price change. 0.25 is the value which we would obtain by random change, thus we expect to get values higher than this. The higher the value of Ψ the more predictable the price formation process is, in contrast with the entropy rate, where the opposite is true. Details about this method and its behaviour on the markets as a whole can be found in a study by Fiedor (2014b).

Experimental results

For this study we have chosen 50 companies which have filed for bankruptcy in the years between 2011 and 2013. All these have ended with a decision before the end of February 2014. The full list of the studied companies can be found in Appendix A. For all of these companies we have obtained their full price history (http://bossa.pl/notowania/pliki/intraday/omega/), and constructed times series containing intraday logarithmic price changes (at the level of transactions), and we have further discretised them into four states (quartiles). In the presented results we do not use all 50 companies, as some were discarded due to having too short time series for a given analysis. In most cases over 40 companies were analysed (with the lowest value of 32 for the analysis around the decision date with running window of length 100). Companies were not discarded from the analysis for any other reason than lack of appropriate length of time series needed for the analysis at hand. Here we note that due to having transaction data we do not use real time, and instead all analyses are based on event time (every price change equals one time step). We calculate both $\hat{H}_{lz}$ and Ψ with a running window approach of a given length, going through the whole series. We attribute the value for a given window to the date of the last observation in this window, so that the value for a given date does not contain any future data. We have considered various lengths of running window, and as these do not change the results drastically we present two opposite ends (30 and 100 price changes). We do not consider windows shorter than 30 price changes due to the needs of the used estimators, and longer than 100 price changes, as such analysis would lose sight of the temporal changes which we want to find.

First, we want to investigate whether the predictability of price formation processes of the studied companies changed with regards to the date of the motion for bankruptcy and the date of the decision regarding bankruptcy. For this purpose we have compared $\hat{H}_{lz}$ and Ψ averaged over all windows of length of 30 price changes assigned to the dates before and after the motion and decision dates. We present the average difference between the two (together with one standard deviation), divided into specific groups of companies, in Table 1. There, $\hat{H}_{lz}$ is denoted as LZ and Ψ as MEPP. The numbers in brackets denote the number of companies included in the analysis around the particular date, and in given groups (around motion date/around decision date). As can be seen some companies have been excluded due to too short time series. It is worth noting that while a positive change in $\hat{H}_{lz}$ denotes increase in predictability, a positive change in Ψ would usually be associated with decrease in predictability. The values for the whole set can be aggregated from the groups, which give insight into what particular factors around the bankruptcy may affect changes in predictability. In particular, we distinguish between companies from the construction sector and companies from all other sectors, as there has been a large number of bankruptcies in this particular sector in Poland. We also distinguish between arrangement bankruptcy and liquidation bankruptcy, both around the motion and final decision. Further, we also distinguish between stocks listed on the main Polish stock market (GPW, WSE), and Warsaw's alternative market – New Connect (NC). Finally, we distinguish between companies which use International Financial Reporting Standards (IFRS) in their reporting, and ones which prepare their reporting based on Polish law (The Accounting Act). The

Table 1: Average change (with standard deviation) in log returns predictability between windows before and after motion and decision dates (running window of length 30)

Group	Motion date (41)				Decision date (35)			
	MEPP		LZ		MEPP		LZ	
	Av	SD	Av	SD	Av	SD	Av	SD
Construction sector (13/13)	0,1	0,08	-0,29	0,2	0,09	0,07	-0,32	0,17
Other sectors (28/22)	0,08	0,11	-0,28	0,23	0,06	0,12	-0,32	0,26
Arrangement bankruptcy motion (28/25)	0,08	0,1	-0,26	0,23	0,06	0,1	-0,27	0,24
Liquidation bankruptcy motion (13/10)	0,18	0,03	-0,42	0,16	0,08	0,12	-0,57	0,01
GPW (21/21)	0,09	0,11	-0,29	0,25	0,07	0,11	-0,28	0,25
NC (20/14)	0,08	0,1	-0,26	0,19	0,05	0,11	-0,25	0,17
IFRS (19/19)	0,09	0,11	-0,28	0,25	0,06	0,11	-0,28	0,26
Polish accounting (22/16)	0,09	0,1	-0,29	0,19	0,08	0,11	-0,37	0,16
Arrangement bankruptcy decision (16/10)	0,08	0,09	-0,27	0,16	0,05	0,1	-0,4	0,14
Liquidation bankruptcy decision (18/18)	0,09	0,11	-0,29	0,25	0,08	0,11	-0,28	0,26

Source: Authors' compilation

Table 2: Average change (with standard deviation) in log returns predictability between windows before and after motion and decision dates (running window of length 100)

Group	Motion date (41)				Decision date (35)			
	MEPP		LZ		MEPP		LZ	
	Av	SD	Av	SD	Av	SD	Av	SD
Construction sector (13/13)	0,09	0,08	-0,42	0,29	0,06	0,11	-0,45	0,27
Other sectors (28/22)	0,09	0,09	-0,38	0,28	0,05	0,12	-0,45	0,27
Arrangement bankruptcy motion (28/25)	0,07	0,08	-0,38	0,31	0,03	0,11	-0,42	0,31
Liquidation bankruptcy motion (13/10)	0,19	0,03	-0,42	0,37	0,08	0,19	-0,65	0,09
GPW (21/21)	0,08	0,1	-0,44	0,3	0,07	0,1	-0,45	0,32
NC (20/14)	0,09	0,08	-0,29	0,26	0,02	0,14	-0,28	0,16
IFRS (19/19)	0,08	0,1	-0,41	0,31	0,07	0,1	-0,42	0,33
Polish accounting (22/16)	0,1	0,08	-0,38	0,27	0,03	0,14	-0,48	0,17
Arrangement bankruptcy decision (16/10)	0,1	0,08	-0,32	0,27	0	0,15	-0,46	0,17
Liquidation bankruptcy decision (18/18)	0,09	0,1	-0,48	0,3	0,08	0,1	-0,48	0,32

Source: Authors' compilation

same results for windows of length of 100 price changes have been presented in Table 2.

As the results above deal with changes for dates which may reach very far before and after the studied dates we want to check whether eventual changes in predictability are rapid, i.e. occurring very close to the motion or decision dates. For this purpose we present the same differences as above, but between $\hat{H}_{lz}$ and Ψ averaged over all windows of length of 30 price changes assigned to the dates of 30 days before and after the motion and decision dates. This has been presented in Table 3. Further, the same results obtained using running window of length of 100 price changes have been presented in Table 4. Due to various trading activity (particularly lack thereof in some cases) within a month of the studied dates there is a different number of studied companies in this case, as compared to the above analysis of all dates before and after the studied motion and decision dates.

To complete the analysis, we also show the changes in $\hat{H}_{lz}$ in time for three companies. These have been chosen so that we have one company with a motion date

Table 3: Average change (with standard deviation) in log returns predictability between windows 30 days before and after motion and decision dates (running window size 30)

Group	Motion date (33)				Decision date (32)			
	MEPP		LZ		MEPP		LZ	
	Av	SD	Av	SD	Av	SD	Av	SD
Construction sector (12/12)	0,07	0,14	-0,08	0,25	-0,01	0,08	-0,05	0,16
Other sectors (21/20)	0,03	0,13	-0,11	0,24	-0,03	0,11	-0,09	0,28
Arrangement bankruptcy motion (24/23)	0,06	0,14	-0,08	0,26	-0,02	0,1	-0,07	0,27
Liquidation bankruptcy motion (9/9)	0,02	0,05	-0,1	0,13	-0,1	0,08	-0,07	0,06
GPW (19/19)	0,05	0,11	-0,13	0,24	0	0,08	-0,04	0,19
NC (14/13)	0,03	0,16	-0,06	0,25	-0,04	0,12	-0,08	0,31
IFRS (18/18)	0,07	0,11	-0,15	0,25	-0,01	0,09	-0,04	0,21
Polish accounting (15/14)	0,02	0,15	-0,05	0,24	-0,04	0,12	-0,12	0,29
Arrangement bankruptcy decision (15/16)	-0,01	0,09	-0,06	0,14	-0,05	0,09	-0,07	0,16
Liquidation bankruptcy decision (11/9)	0,1	0,14	-0,08	0,28	-0,03	0,07	-0,01	0,25

Source: Authors' compilation

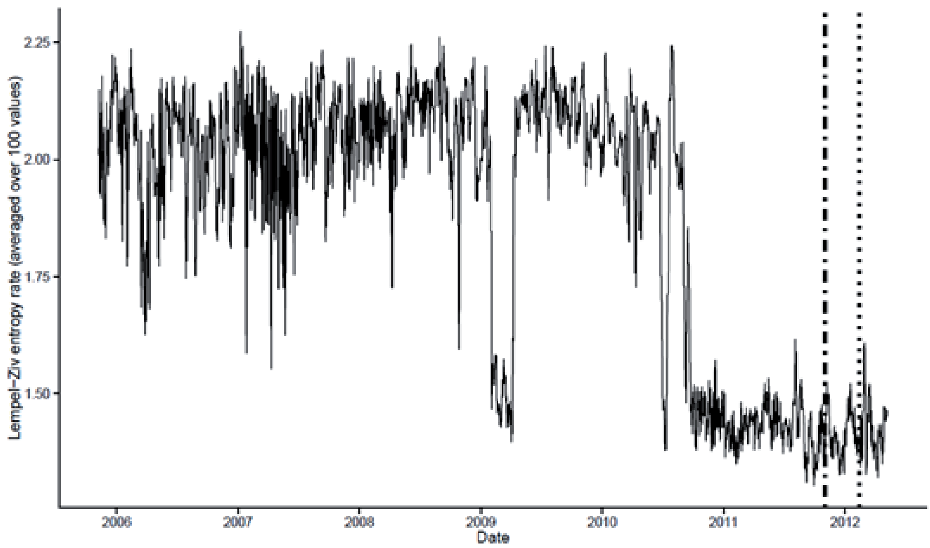
Table 4: Average change (with standard deviation) in log returns predictability between windows 30 days before and after motion and decision dates (running window size 100)

Group	Motion date (33)				Decision date (32)			
	MEPP		LZ		MEPP		LZ	
	Av	SD	Av	SD	Av	SD	Av	SD
Construction sector (12/12)	0,02	0,18	-0,17	0,21	-0,02	0,1	-0,04	0,14
Other sectors (21/20)	0,06	0,11	-0,15	0,2	-0,01	0,16	-0,06	0,2
Arrangement bankruptcy motion (24/23)	0,04	0,14	-0,15	0,21	-0,01	0,14	-0,06	0,2
Liquidation bankruptcy motion (9/9)	0,03	0,08	-0,18	0,21	-0,12	0,19	-0,03	0,07
GPW (19/19)	0,07	0,11	-0,17	0,22	0,02	0,1	-0,06	0,21
NC (14/13)	0,01	0,15	-0,12	0,19	-0,05	0,17	-0,02	0,12
IFRS (18/18)	0,08	0,11	-0,21	0,21	0,03	0,1	-0,06	0,22
Polish accounting (15/14)	0,01	0,15	-0,1	0,19	-0,07	0,16	-0,03	0,11
Arrangement bankruptcy decision (15/16)	0,01	0,15	-0,12	0,19	-0,12	0,16	-0,05	0,07
Liquidation bankruptcy decision (11/9)	0,06	0,11	-0,17	0,2	0	0,09	0,01	0,17

Source: Authors' compilation

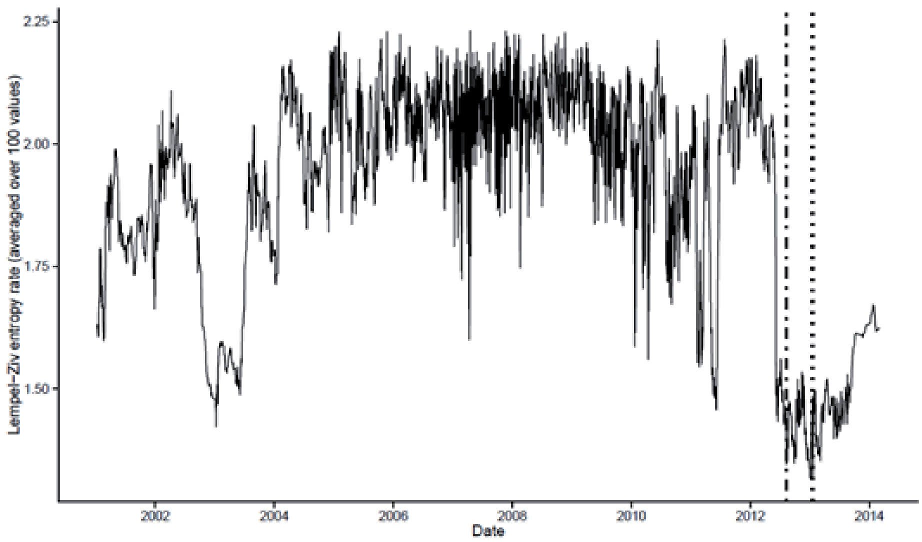
in each of the three studied years (2011-2013), so that we see whether any changes in predictability depend on the dates regarding their bankruptcy, or whether they are related to some external market changes. In each case we have taken a company with the longest time series, so that the results are most statistically robust. Thus for 2011 we have chosen Firma Handlowa Jago SA (JAGO), with motion date on 2nd November 2011, and decision date on 14th February 2012, as presented in Figure 1. Both dates are presented as vertical lines. The presented $\hat{H}_{lz}$ has been further averaged over 100 values to eliminate some statistical noise for presentation purposes. For 2012 we have chosen ENERGOMONTAŻ-POŁUDNIE SA (ENERGOPLD), with motion date on 10th August 2012, and decision date on 18th January 2013, as presented in Figure 2. Finally, for 2013 we have chosen Gant Development SA (GANT), with motion date on 16th October 2013, and decision date on 2nd January 2014, as presented in Figure 3.

Figure 1: Changes in Lempel-Ziv entropy rate averaged over 100 windows in time, with motion and decision dates as vertical lines for JAGO (running window of length 30)



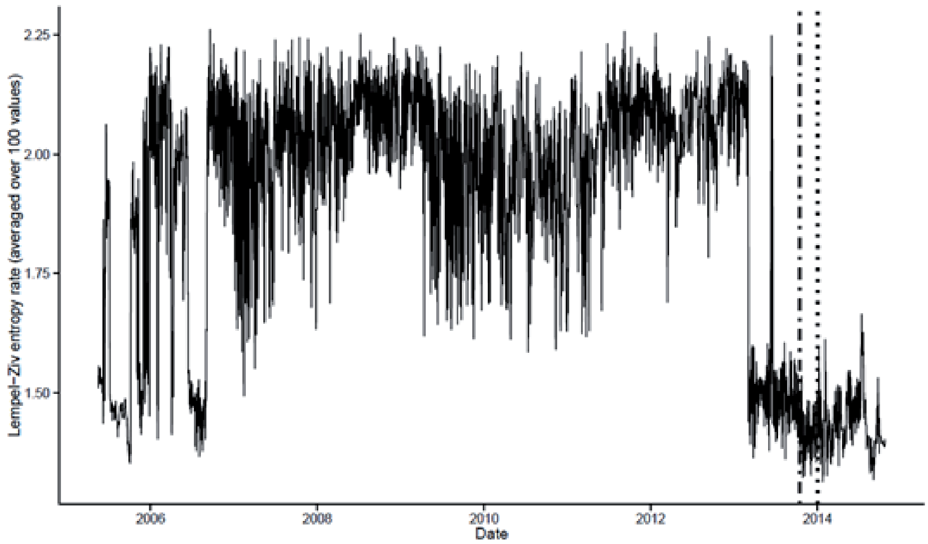
Source: Authors' compilation

Figure 2: Changes in Lempel-Ziv entropy rate averaged over 100 windows in time, with motion and decision dates as vertical lines for ENERGOPLD (running window size 30)



Source: Authors' compilation

Figure 3: Changes in Lempel-Ziv entropy rate averaged over 100 windows in time, with motion and decision dates as vertical lines for GANT (running window of length 30)



Source: Authors' compilation

Discussion

In the discussion of presented results, we first turn to the results presented in Table 1. We see that the difference in predictability (Lempel-Ziv entropy rate) of price formation processes before and after the motion date is equal to −0.29, with standard deviation of 0.22. Thus the price formation processes within the studied companies are more predictable (further from the Efficient-Market Hypothesis) after the motion date. There is no significant difference due to the market the stock is listed on or the sector the stock belongs to, as well as the decision type or accounting standards employed. But there is a significant difference between the type of the motion filed. The change in predictability is much stronger in companies filing for liquidation bankruptcy, which corroborates that the found differences are due to bankruptcy and not other factors, as it is natural since liquidation bankruptcy is the more severe case. This change could still be a part of a global change on the whole market in the studied period, and not related to the bankruptcies. It has been shown that the Polish market was moving towards lower predictability around that time however (Fiedor, 2014c), hinting that the reported changes do stem from the studied bankruptcies. This is also further corroborated by the analysis of the three particular examples, discussed below. The results based on the Maximum Entropy Production Principle show the same picture, with an average increase of the guessing rate of 9% for all companies, and 18% for companies filing for liquidation bankruptcy. If we look at the changes in predictability between dates before and after the decision date then a similar pattern appears, but with some interesting changes. The average difference for all companies equals to −0.32, with standard deviation of 0.23. Again, this change is more severe for companies filing for liquidation bankruptcy. Curiously, this change also appears stronger for companies with decision of arrangement bankruptcy, compared with those with decision of liquidation bankruptcy. The change is also stronger for companies using reporting based on Polish accounting law, as compared with those using IFRS. These differences are less clear when looking at the differences using the Maximum Entropy Production Principle however, and also inconsistent with the analyses below, thus we do not treat them as strong conclusions.

Looking at Table 2, which shows the results obtained with running window of length 100 price changes, it is worth noting that the general results remain the same, i.e. the price formation processes are more predictable after the motion and decision dates. There are differences in the details however. First, this change equals −0.39, with standard deviation of 0.28 for motion date, and −0.45, with standard deviation of 0.27 for decision date. We still see a large difference between these changes for companies which filed for arrangement and liquidation bankruptcies. The other group comparisons are either not statistically significant, or are inconsistent between studied time windows or used methods. Thus we conclude that the bankruptcies make price formation processes more predictable, and particularly so for companies filing for liquidation bankruptcies. This change is also slightly stronger for companies listed on the main stock market, perhaps due to more investor interest, and also stronger around the decision date for companies operating on Polish accounting/reporting standards, hinting that perhaps IFRS reporting leaves less doubt about the economic situation of these companies even before it is obvious.

We turn to Tables 3 & 4 to find out whether these long term effects studied above are accompanied by rapid changes around the motion and decision dates (within 30 days before and after). For the results based on a running window of length 30 price changes (Table 3) we see that there is no such rapid impact on the predictability of price formation processes. While the results tend to still be negative on average for Lempel-Ziv entropy and positive on average for Maximum Entropy Production Principle, these are insignificant when looking at the associated standard deviation (average change of −0.1, with standard deviation of 0.24 for Lempel-Ziv entropy rate around the motion date, and average change of −0.07, with a standard deviation of 0.24 for Lempel-Ziv entropy around the decision date). Looking at Table 4, which shows a slightly less rapid version (as using running window of length of 100 price changes) these changes start to appear stronger, but are still relatively weak compared to their standard deviation (with average change of −0.16, with standard deviation of 0.2 for Lempel-Ziv entropy rate around the motion date and average change of −0.05, with a standard deviation of 0.18 for Lempel-Ziv entropy around the decision date). We thus conclude that while bankruptcies affect the predictability of price formation processes, these changes are not rapid around the motion and decision dates, and instead happen in a mid-term perspective, hinting that the situation of the companies is within the grasp of knowledge of the investors, at least to some degree, before the companies present the motion for bankruptcy.

Finally, we look at the three specific cases, presented in Figures 1-3. As can be seen the predictability changes drastically (decreasing) before the motion date. This happens either directly before the motion date (ENERGOPLD) or several months before (other two cases). What is important is that this shift in predictability happens at various dates, thus hinting that these are not related to some external event on the Warsaw market, but are related specifically to these bankruptcies. These changes do not fall in the same part of the year, either for these three companies, or other studied companies, thus they do not appear to be related to yearly reporting, and rather to investors' information about the economic state of the companies from other sources.

Conclusions

In this study we have investigated whether the predictability (efficiency as in the Efficient-Market Hypothesis) of price formation processes is changed by bankruptcies on Warsaw's Stock Exchange. We have estimated this predictability using Lempel-Ziv entropy rate, together with a related practical prediction scheme (Maximum Entropy Production Principle). Our results indicate that the predictability of price formation processes strongly increases with regards to the motion date of bankruptcy (and also, secondarily, around the decision date), and in fact usually changes in this fashion months before this date, hinting that the investors have knowledge of the economic situation of these companies which affect the efficiency of their price formation processes on the stock market. We have found little evidence of various factors affecting this, except for the type of bankruptcy for which the company is filing. This effect appears to be much stronger for companies filing for liquidation bankruptcy. Further studies should look into such effects on other financial markets, particularly mature markets such as the New York Stock Exchange.

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Appendix A

Table 5: List of studied companies

A.pl Internet SA	Cash Flow SA	Firma Handlowa Jago SA	Mediatel SA	R&C Union
ABM Solid SA	Cool Marketing SA	Fota SA	Mew SA	Religa Development SA
Advadis SA	D&D SA	Gant Development SA	Motor Trade Company SA	Richter Med SA
Alterco SA	Direct eServices SA	GREENECO SA (Anti)	Nicolas Entertainment Group SA	Sobet SA
BGE SA	Dolnośląskie Surowce Skalne SA	Hydrobudowa Polska SA	OEM SA	SSI SA
Bomi SA	Drewex SA	Ideon SA	Partex SA	Synkret SA
BUDOPOL-WROCŁAW SA	ENERGOMONTAŻ-POŁUDNIE SA	Intakus SA	PBG SA	TimberOne SA
Budostal-5 SA	Euromark Polska SA	Internetowy Dom Zdrowia SA	Polskie Jadło SA	Waspol SA
BUDUS SA	Europejski Fundusz Hipoteczny SA	InwazjaPC SA	Positive Advisory SA	Wilbo SA
Call2Action SA	Fabryka Maszyn Ożarów SA	KCSP SA	Promet SA	ZOO Centrum SA

Source: Authors' compilation