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Marcin Czupryna
Elżbieta Kubińska
Łukasz Markiewicz

ON THE NEED FOR COGNITIVE CLOSURE AND JUDGMENTAL TREND FORECASTING

Abstract

The paper considers the following hypothesis: humans' need for cognitive closure reduces the usage of historical observations in judgmental forecasts only in horizontal trends. To test this hypothesis, three studies were conducted. In each, participants forecasted the next, unknown observation using the previous time series. The analysis concentrated on trend analysis and how the trends in historical data are used as the basis for forecasting depending on psychological traits, in particular cognitive closure.

Keywords: judgmental forecast, need for cognitive closure, time series analysis, trend identification.
JEL Classification: G410, C580.

1. Introduction

A great deal has been written on whether a judgmental forecast provides value added to statistical forecasts (see e.g. Lawrence et al. 2006). Numerous factors may influence judgmental forecasts, including external factors such as how a time series is presented (Weber at al, 2005), its statistical properties (e.g. its variability) and the characteristics of the person giving

Marcin Czupryna, Cracow University of Economics, Faculty of Finance and Law, Department of Financial Markets, Rakowicka 27, 31-510 Kraków, Poland, e-mail: czuprynm@uek.krakow.pl

Elżbieta Kubińska, Cracow University of Economics, Faculty of Finance and Law, Department of Financial Markets, Rakowicka 27, 31-510 Kraków, Poland, e-mail: kubinska@uek.krakow.pl

Łukasz Markiewicz, Kozminski University, Department of Economic Psychology, Jagiellońska 57/59, 03-301 Warszawa, Poland, e-mail: lmarkiewicz@kozminski.edu.pl

the prognosis, including his or her expertise and psychological traits. In this research we concentrate on the influence individual differences exert on judgmental forecasting. Previous studies have shown that both individual differences and perception of the nature of the phenomenon that generates the outcome (i.e. whether it depends on human skills or randomness) influence the process of trend identification (Tyszka et al. 2017). While one would assume that higher expertise should lead to better forecasts, there is the empirical evidence to the contrary, e.g. J. F. Yates, L. S. McDaniel and E. S. Brown (1991). In their between-the-subject research, they showed that undergraduate students outperformed graduate students in forecast accuracy. Yates et al. explained that the graduates students had greater expertise in economics and were therefore more prone to include in their forecasts factors that in fact had no additional explanatory power. The other aspect of judgmental forecasting is historical data. Based on the literature and the results of multiple regressions, P. Goodwin (2005) reports that a heuristic for forecasting is to include the last observation and the mean of the most recent observations for untrended series, and to include the last observation and the trend for trended series.

We have simulated an experimental environment that takes into account different historical trends and different degrees of information availability. Instead of having two groups of participants with different levels of expertise forecast the same time series (between the subjects) as Yates et al. did, we asked the same group of participants to forecast two different time series (within the subject). One of them, the stock exchange index, would have been perceived as domestic, so additional information was available to them (macroeconomic, political, experts opinions) while for the other, a foreign stock exchange index, they had less information.

2. The Need for Cognitive Closure

Some individual differences may influence the forecast reliance on the historical time series data and thus its ability and correctness. A. W. Kruglanski (1989, p. 14) introduced to psychology the concept of the need for cognitive closure, which he defined as “the desire for a definite answer on some topic, any answer as opposed to confusion and ambiguity”. Thus, one with a strong need for cognitive closure demonstrates a strong desire for a clear-cut opinion, reached by obtaining an answer – any answer – even one that is not the most optimal or correct. Thus, such individuals are assumed to refrain from processing further information as soon as they have closure (any answer). As a result, individuals with a strong need for cognitive closure are more likely to use early information in forming judgments, rendering their information processing more superficial. On these grounds, we suspect that the need for cognitive closure leads to a tendency to skip trend analysis (as a method of information simplification) or at the very least a tendency to look for trends in short periods rather than long ones. These individuals finish processing information faster, after an initial check provides sufficient confirmation. Individuals with a strong need for cognitive closure have a strong preference for order and structure and a strong desire for predictability, feel discomfort when confronted with ambiguity and are close-minded – with respect to all of the aspects covered in Kruglanski's need-for-closure scale.

The goal of this paper is to verify how individual differences influence judgmental forecasting. We first analyse the relationship between inclusions of the historical observation in judgmental forecasts depending on individual differences. We then verify these relationships for time series moving in three directions: in an upwards, sideways or downwards trend. We hypothesise that the need for cognitive closure plays an important role in making judgmental forecast in sideways trends, but not in upwards or downwards ones: the need for cognitive closure reduces the usage of historical observations in judgmental forecasts only in sideways trends.

The paper is organised as follows. We first analyse the statistical properties of forecasted time series and present the study. We then analyse the relations between psychological traits and the forecasting process.

3. Method

We have conducted three independent studies; two of them were based on real data from the WIG and DAX indexes. These are, respectively, Study 1A and Study 1B. The last study (Study 2) was based on synthetic data generated using an assumption on the underlying autoregressive stochastic process for rates of return.

Participants

Students of the Capital Markets major of Cracow University of Economics participated in this study during a one-semester Technical Analysis course. Participation was voluntary; however, participating students were given bonus credits for the Technical Analysis course. Additionally, students were awarded extra bonus credits depending on their results. This was intended to provide higher motivation than any minor monetary payoffs that might have been offered instead[1]. One group of students participated in Study 1A, while the second independent group of students participated in Studies 1B and 2. There was a two-year interval between Study 1 and the other studies in order to minimise the information flow to the next year younger students from their older colleagues. Table 1 presents the demographic characteristics of the participants. At an average age of 22, the participants were young. As can also be seen, men were in the majority in all three studies.

Table 1. Demographic Data on the Groups of Students Participating in Studies 1A, 1B and 2

Studies	N	Number of		Age	
		Women	Men	Mean	Standard deviation
1A	58	18	40	22,57	3,24
1B & 2	66	21	45	22,29	2,90

Source: the authors' own study.

Materials – Studies 1A and 1B

Participants of Studies 1A and 1B completed a battery of psychological tests on individual differences for the assessment of information processing and cognitive preferences. Among them there was a 15-item version of the Need For Closure Scale – NFCS (see Webster & Kruglanski 1994, Roets & Van Hiel 2011) covering the following subscales:

– desire for predictability (NFC_FP),
– preference for order and structure (NFC_OP),
– discomfort with ambiguity (NFC_MI),
– decisiveness (NFC_BD),
– close-mindedness (NFC_CC).

Procedure – Studies 1A and 1B

In studies 1A and 1B, the students were asked to regularly provide forecasts for the forthcoming week's rate of returns for the WIG and the DAX. Within each study the participants were randomly assign to two groups, one that forecast the WIG and the other the DAX. Study 1A was

[1] Students receive the monthly scholarship depending on their average grade, so there is a direct relationship between grades and payments. Moreover, a good average grade is very important for the third year students as it allows them to avoid taking the entrance exams for their MA studies.

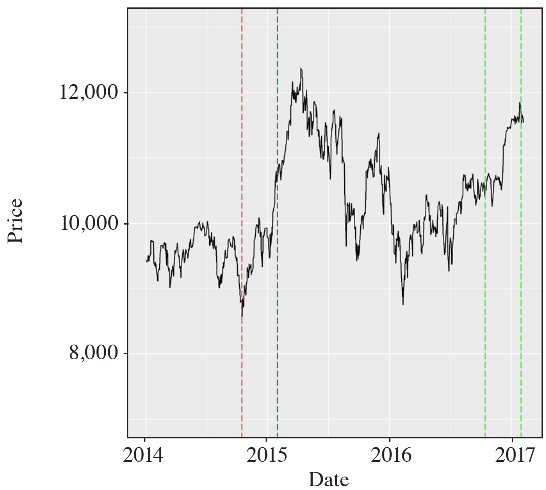

Fig. 1. DAX Index Time Series

Note: the red lines represent the timing of Study 1A, and the green lines the timing of Study 1B.
Source: the authors' own elaboration.

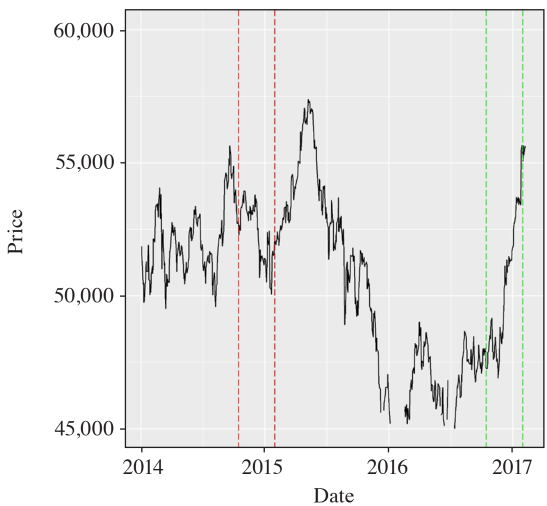

Fig. 2. WIG Index Time Series

Note: the red lines represent the timing of Study 1A, and the green lines the timing of Study 1B.
Source: the authors' own elaboration.

conducted each week, from 1 October 2014 until 8 February 2015, while Study 1B ran from 10 October 2016 to 30 January 2017. The time series to be forecast are presented in Figures 1 and 2. The time period of the Study 1A is shown between the red dotted lines and Study 1B between the green dotted lines.

The study was conducted in a LimeSurvey during the classes. The students had access to historical prices of the DAX and WIG. In particular, we asked for a point forecast r_f and the students were told that at the end of the semester the mean absolute deviation from the real observed rates of return would determine the number of extra credit points they received for the course. The top 30% of the students received 3 points, the next 40% 2 points, the next 20% 1 point, and the lowest 10% no extra points.

Materials and Procedure – Study 2

During the semester, between 6 November 2016 and 15 January 2017, we conducted five independent studies. The same group of students that participated in Study 1B was asked to provide forecasts for synthetically generated time series. The study was21 conducted in LimeSurvey. Students were presented graphs (like the one in Figure 3) and in some studies also histograms of the weekly rate of returns and data. The parameters in nine (three by three) studies are identical as the studies differed only with respect to information availability: graph, graph plus histogram and graph plus histogram plus raw data.

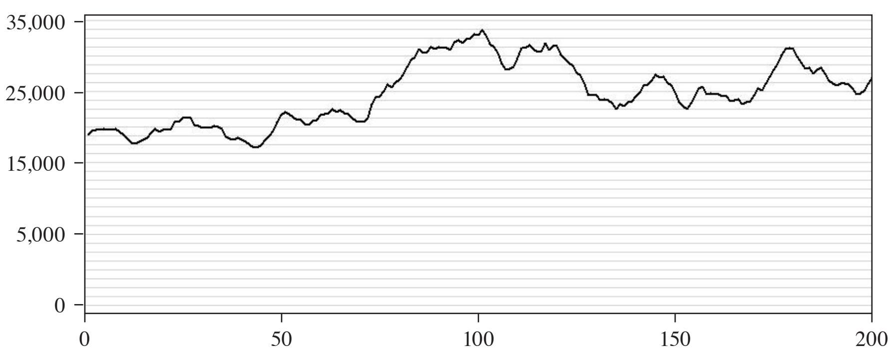

Fig. 3. Example of the Time Series Presented to the Students in Study 2

Source: the authors' own elaboration.

4. Results

Studies 1A and 1B

First we used Alexander filter (as implemented in R with ttr-package) with different parameters – 20%, 10%, 5% and 2.5% – to identify the trends in the forecast time series, for each index and each forecast period. The 20% parameter enabled the identification of the longer time trends while the 2.5% parameter enabled the identification of the shorer ones. We used different parameters as we did not know which time perspective the students were using for their forecasts. The filter enables the identification of local extremes (minimum and maximum). We have defined the current trend as the average daily logarithmic return from the last identified extreme price until the forecast day. If this period was too short (shorter than 10 days for 20%, 10% and 5% parameters and 5 days for 2.5% parameter), the second last identified extreme was considered instead. The correlations of forecast returns with identified last trend returns for different time perspective were then calculated. The trend with the highest absolute correlation with the forecast was finally chosen for further analysis. The absolute value of the correlation between the selected trend value and the relevant point forecast is denoted *RR*. The variable *PER.* denotes the correlation with the trend period (and has the following values: 1 – 20%, 2 – 10%, 3 – 5% and 4 – 2.5%) and relevant forecasting variable. A positive value means that the students tended to use shorter trends for their forecasts. Thus we could identify not only which time perspective (longer or shorter) the student considered for their forecast but also to what extent. Second, because we were only investigating if the students use trends for their forecast, and not how they use them, we used the absolute value in order to treat the momentum (the forecast with the trend) and contrarian (the forecast against the trend) strategies as equal.

Analogue results for Study 1B are shown in Table 3.

To combine the results, we apply Stouffer's *Z*-score method. The results of the one-sided test are shown in Table 4.

In Study 1A we can observe that students with higher levels of order preference (*OP*) and desire for predictability (*FP*) use the identified trends for prediction to a lesser extent. The results of Study 1B did not confirm this result, as the relationship between the NFC subscales and the use of trends for forecasting is not significant in Study 1B.

Table 2. Correlation Coefficients between the Analysed Variables for Study 1A

Study 1A	DAX			WIG			*OP*	*FP*	*MI*	*CC*	*BD*
	RR	*PER.*	*TIME*	*RR*	*PER.*	*TIME*					
RR	1	0.07	0	1	0	0.14	–0.22	–0.17	–0.18	0.09	0.14
PER.	0.07	1	–0.1	0	1	0.17	0.04	–0.14	–0.1	0.07	0.11
TIME	0	–0.1	1	0.14	0.17	1	–0.02	0.01	–0.03	–0.14	0.04
OP	–0.22	0.04	–0.02	–0.2	–0.09	–0.02	1	0.6	0.47	–0.17	–0.02
FP	–0.17	–0.14	0.01	–0.24	–0.05	0.01	**0.6**	1	0.64	0.03	–0.14
MI	–0.18	–0.1	–0.03	–0.19	–0.01	–0.03	**0.47**	**0.64**	1	–0.18	–0.16
CC	0.09	0.07	–0.14	–0.14	0.04	–0.14	–0.17	0.03	–0.18	1	0.25
BD	0.14	0.11	0.04	–0.17	0.16	0.04	–0.02	–0.14	–0.16	**0.25**	1

Note: *RR* – forecast value, *PER.* – period of the trend considered in forecasting, *TIME* – average time used to prepare the forecasts and the psychological trait measured by the need for cognitive closure subscales tests (*OP* – preference for order and structure, *FP* – desire for predictability, *MI* – discomfort with ambiguity, *CC* – close-mindedness, *BD* – decisiveness). Significant values of correlation coefficient are bold (p-value < 0.05).

Source: the authors' own study.

Table 3. Correlation Coefficients between the Analysed Variables for Study 1B

Study 1B	DAX			WIG			*OP*	*FP*	*MI*	*CC*	*BD*
	RR	*PER.*	*TIME*	*RR*	*PER.*	*TIME*					
RR	1	–0.04	0.2	1	0	0.1	0.13	0.02	0.1	–0.16	0.15
PER.	–0.04	1	–0.22	0	1	0.12	0.03	0.12	–0.07	–0.06	0.07
TIME	0.2	–0.22	1	0.1	0.12	1	0	–0.09	0.06	–0.03	–0.29
OP	0.13	0.03	0	0.21	–0.01	–0.05	1	0.55	0.42	–0.13	0.12
FP	0.02	0.12	–0.09	0.02	–0.1	–0.2	**0.55**	1	0.52	–0.05	–0.04
MI	0.1	–0.07	0.06	**0.25**	–0.25	0.07	**0.42**	**0.52**	1	–0.06	–0.25
CC	–0.16	–0.06	–0.03	0.03	–0.11	–0.07	–0.13	–0.05	–0.06	1	0.11
BD	0.15	0.07	**–0.29**	–0.08	0.09	**–0.3**	0.12	–0.04	**–0.25**	0.11	1

Note: *RR* – forecast value, *PER.* – period of the trend considered in forecasting, *TIME* – average time used to prepare the forecasts and the psychological trait measured by the need for cognitive closure subscales tests (*OP* – preference for order and structure, *FP* – desire for predictability, *MI* – discomfort with ambiguity, *CC* – close-mindedness, *BD* – decisiveness). Significant values of correlation coefficient are bold (p-value < 0.05).

Source: the authors' own study.

Table 4. One-sided p-values of the Estimated Correlation Coefficients between Absolute Values of Correlation Coefficients between the Observed Trend and the Forecast Value and the Need for Cognitive Closure Subscales Tests (NFCS) for Studies 1A and 1B

Study	Preference for order and structure (*OP*)	Desire for predictability (*FP*)	Discomfort with ambiguity (*MI*)	Close--mindedness (*CC*)	Decisiveness (*BD*)
1A	0.0443	0.0561	0.0796	0.3413	0.169
1B	0.1081	0.9553	0.0894	0.5202	0.3424

Source: the authors' own study.

Table 5. The Number of Local Optima (Minimum or Maximum) for Different Parameters of the Alexander Filter as Well as the Total Rate of Return in the Period Considered

Exp.	20%	10%	5%	2.5%	*RR*
1	4	9	18	22	0.29
2	4	7	21	29	–0.5
3	2	7	17	44	0.08
4	7	9	9	19	–1.12
5	2	8	13	31	1.08
6	2	6	14	34	0.01
7	4	10	14	26	0.05
8	4	8	12	26	0.92
9	2	9	17	33	–0.35
10	4	8	13	21	–0.73
11	4	7	19	27	0.28
12	1	5	11	32	0.29
13	7	15	23	45	1.05
14	5	16	24	34	1.36
15	7	17	33	57	0.35
16	7	15	23	45	1.05
17	5	16	24	34	1.36
18	7	17	33	57	0.35
19	7	15	23	45	1.05
20	5	16	24	34	1.36
21	7	17	33	57	0.35

Source: the authors' own study.

Study 2

The Alexander filter was used for the randomly generated time series used in Study 2. The number of single rounds of the experiment as well as the number of local optima (minimum or maximum of the time series, sometimes called support and resistance) for different parameters of the Alexander filter as well as the total rate of return in the period considered are presented in Table 5. The parameters in the last nine (three by three) studies are identical as the studies differed only with respect to the availability of information: graph, graph plus histogram and graph plus histogram plus raw data.

We next selected the study rounds for the sideways trends (the rate of return value in the whole period considered between –30% and 30%) and the rounds in dominating upwards or downwards trends (the rate of return value in the whole period considered lower than –70% or higher than 70%). The results are presented in Table 6.

Table 6. Correlation Coefficients between the Analysed Variables for Study 2

Study 2	Sideway trend			Up or down trend			*OP*	*FP*	*MI*	*CC*	*BD*
	RR	*PER.*	*TIME*	*RR*	*PER.*	*TIME*					
RR	1	0.02	0.23	1	0.64	–0.14	–0.02	–0.44	–0.11	–0.03	0.15
PER.	0.02	1	0.3	**0.64**	1	–0.04	0.51	0.17	0.2	0.2	–0.11
TIME	0.23	0.3	1	–0.14	–0.04	1	0.22	–0.12	0.1	0.11	–0.29
OP	–0.02	**0.51**	0.22	0.2	0.27	0.28	1	0.56	0.42	–0.15	0.14
FP	**–0.44**	0.17	–0.12	–0.09	0.04	0.09	**0.56**	1	0.53	–0.07	–0.06
MI	–0.11	0.2	0.1	–0.05	–0.01	0.28	**0.42**	**0.53**	1	–0.06	–0.25
CC	–0.03	0.2	0.11	–0.07	0.02	0.1	–0.15	–0.07	–0.06	1	0.05
BD	0.15	–0.11	–0.29	**0.48**	**0.49**	–0.18	0.14	–0.06	**–0.25**	0.05	1

Note: *RR* – forecast value, *PER.* – period of the trend considered in forecasting, *TIME* – average time used to prepare the forecasts and the psychological trait measured by the need for cognitive closure subscales tests (*OP* – preference for order and structure, *FP* – desire for predictability, *MI* – discomfort with ambiguity, *CC* – close-mindedness, *BD* – decisiveness). Significant values of correlation coefficient are in bold (p-value < 0.05).

Source: the authors' own study.

There are significant differences in the sideways and dominant up or downtrends. A desire for predictability (*FP*) compels students not to use trends in sideways trend situations as the basis for forecasting. However, that desire has no impact in dominant trends. This confirms the observation we had when the WIG and DAX indices were forecast. In the timeframe of Study 1A, both markets were in sideways trends, while in the timeframe of Study 1B both were in a dominant uptrend. Finally, decisiveness (*BD*) led the students to use trends for forecasting to a larger extent.

5. Conclusions

We have confirmed the following hypothesis in this paper: the need for cognitive closure reduces the usage of historical observations in judgmental forecasts only in the case of side-ways trends. Using synthetic data, we have explained the phenomenon observed in this paper – the desire for predictability leads people to forego using trends or not to look for secondary trends when the market trend is sideways. On the other hand, when the trends are upward or downward, decisiveness compels people to use trends such as forecasting as a foundation, which may lead them to take too much risk. Further research will consider a study with synthetic data that differs with respect to the overall trend (rate of return) and frequency of local minima and maxima.

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Abstract

O potrzebie domknięcia poznawczego i prognozowania trendu

W artykule została przedstawiona hipoteza, że potrzeba domknięcia poznawczego wpływa na ograniczone wykorzystanie informacji ujętych w historycznych danych podczas tworzenia prognoz tylko w przypadku trendów bocznych. W celu weryfikacji tej hipotezy zrealizowano trzy eksperymenty, w każdym z nich uczestnicy prognozowali przyszłą wartość na podstawie dostępnego szeregu czasowego. Skupiono się na analizie trendów. Zbadano, w jaki sposób trendy w danych historycznych są wykorzystywane jako podstawa tworzenia prognoz w zależności od psychologicznych inklinacji, w szczególności potrzeby domknięcia poznawczego.

Słowa kluczowe: prognozowanie, potrzeba domknięcia poznawczego, analiza szeregów czasowych, identyfikacja trendu.