Ekonomický časopis, *63*, 2015, č. 6, s. 599 – 616

Naïve Investment Strategies in Complex Financial Choices[1]

Vladimir BALÁŽ – Viera BAČOVÁ***

Abstract

This study analysed efficiency of heuristic strategies in complex financial choices. Some 200 naïve investors evaluated 15 financial products with eight attributes. Complex choices developed in two stages. Stage one employed non--compensatory strategies for reducing information burden, eliminating inadequate options and specifying a more narrow decision set. Attribute-based compensatory strategies accounted for a significant majority of strategies in stage two. Naïve decision strategies worked relatively well. Average Sharpe ratios and product ranks were higher than random choices of financial products. The best results were delivered by the normative strategy, however, at the cost of a high information burden.

Keywords: *financial choice, naïve strategies, efficiency of heuristics*

JEL Classification: D14, D81, G02

1. Introduction

1.1. Normative and Heuristic Decision Strategies in Simple and Complex Choices

What types of strategies do complex financial decisions require? Should it be a normative comprehensive strategy, such as weighted added strategy (WADD), or is sort of fast and frugal heuristics sufficient?

Non-normative heuristic strategies are praised for their ecological rationality. It has been observed that fast and frugal strategies may help solve even complex problems with excellent ratio of cognitive effort and accuracy of results

* Vladimir BALÁŽ, Institute for Forecasting, Slovak Academy of Sciences, Šancová 56, 813 64 Bratislava, Slovak Republic; e-mail: vbalaz@yahoo.com

** Viera BAČOVÁ, Institute of Experimental Psychology, Slovak Academy of Sciences, Dúbravská cesta 9, 841 04 Bratislava, Slovak Republic; e-mail: viera.bacova@savba.sk

[1] This work was supported by the Slovak Research and Development Agency under the contract No. APVV-0361-12.

(Gigerenzer, Todd and the ABC Group, 1999). Proponents of simple non-compensatory rules argue that recognition is highly informative in many domains. The power of simple, non-compensatory heuristics (such as recognition) was illustrated and studied predominantly in many low-consequence choices. There is some evidence for the power of simple heuristic strategies in high-consequence decisions. DeMiguel, Garlappi and Uppal (2009) tested naïve 1/*N* portfolio over 14 different optimizing portfolio models. Naïve diversification of total investments to *N* classes of investments generated higher Sharpe ratios[2] than any of the 14 optimizing models. Borges et al. (1999) asked laypeople and experts which US and German companies listed on the stock market they knew. Portfolio based on the recognized stocks performed significantly better than the market indices in period of six months following the interviews. Portfolios based on knowledge of laypeople performed better than those based on knowledge of experts. Borges et al. (1999), however, tested these portfolios over an exceptional and inadequately short period of bull market in 1996 – 1997. In a down market, a high degree of company name recognition led to disappointing investment results, and American investors underperformed on the market (Boyd, 2001). Andersson and Rakow (2007) also did not find support for the claim that a simple strategy of name recognition, used as a general strategy to select stocks, can yield better-than-average returns. They concluded that "selecting stocks on the basis of name recognition is a near-random method of portfolio construction that offers little, if any, benefit to the personal investor" (Andersson and Rakow, 2007, p. 29). An important reservation is that none of the abovementioned studies considered investment costs. The costs may vary substantially across investment products.

Research on efficiency of non-normative heuristics is inconclusive for complex choices. It is generally recognized that the complex choices usually develop in two stages (Payne, 1976, p. 384; Bettman, Luce and Payne, 1998, p. 191). In the first phase, usually a non-compensatory strategy applies, such as *Elimination by Aspects* (EBA; Tversky, 1972), *Lexicographic* (LEX; Fishburn, 1974), or *Recognition Strategy* (REC; Goldstein and Gigerenzer, 2002). The major goal of a non-compensatory strategy is to reduce the initial large set of alternatives. In the second phase, a narrower set of alternatives enables the application of compensatory strategies, such as *Multi-attribute Utility Strategy* (MAUT; Keeney and Raiffa, 1976), *Additive Strategy* (ADD; Tversky, 1969), *Majority of Confirming Dimension* (MCD; Russo and Dosher, 1983) and/or *Majority Strategy* (MAJ; Sen, 1966). In the complex choices, a combination of strategies is much more common than the use of a particular "pure" strategy.

[2] We used the Sharpe rations as the criteria in this research study (see part 2.4).

High-consequence naïve economic strategies may be costly. Abaluck and Gruber (2011) evaluated some 477 thousand of choices available to the elderly across their insurance options under Medicare Part D. A comparison of actual and optimal plans indicated that only some 12% of seniors were able to select the cheapest plan. Their welfare would have been 27% higher if patients had all chosen rationally. Iyengar and Kamenica (2010) presented both laboratory experiments and field data that suggested that the larger choice sets induced a stronger preference for simple, easy-to-understand options ('paradox of choice'). Records of more than half million employees from 638 institutions indicated that the presence of more funds in an individual's 401(k) plan was associated with a higher allocation to less complex products (money market and bond funds) at the expense of equity funds. Paradoxically, with increasing size of the decision set the best option became better, but the average option became worse (Iyengar and Kamenica, 2010, p. 536). Some other studies (e.g. Gärling et al., 2009) have also shown that in many financial decisions people often do not make decisions in their best interest. Kida, Moreno and Smith (2010) however demonstrated that 'paradox of choice' mainly affects less experienced investors, and experienced investors prefer large sets of investment alternatives.

Complex financial decisions require more reasoning then emotional involvement or need to justify. Bettman, Luce and Payne (1998) argue that two preeminent goals for a decision in a complex choice are (i) maximizing the accuracy of the decision and (ii) minimizing the cognitive effort involved in reaching that decision (Bettman, Luce and Payne, 1998, p. 194). We can also assume generally accepted social reasons for the choice: to get a return and to avoid loss. Thus, in case of financial decision making, well-articulated preferences can be assumed.

In the case of familiarity and experience with object preferences, some authors admit that the decision makers use the normative procedure of rational choice (Bettman, Luce and Payne, 1998, p. 188). The final choice, however, may be affected by factors other than the consideration of costs and benefits. The goals of a decision maker (choice accuracy versus effort), complexity of task, framing, wider social context and elicitation of decision-making responses are likely to affect the final decision (Payne, Bettman and Johnson, 1993).

1.2. Identifying Decision Strategies

Identification and classification of decision strategies has presented a great challenge in decision making studies. The first summaries and classifications of decision strategies were developed relatively recently (Payne, 1976; Payne, Bettman and Johnson, 1993; Bettman, Luce and Payne, 1998) and relied on information boards. These strategies were elaborated and extended in the late 2000s (Shah and Oppenheimer, 2008; Riedl, Brandstätter and Roithmayr, 2008) with the help of the Mouselab tracking tools. The Mouselab essentially is a computerized version of information boards. Riedl, Brandstätter and Roithmayr (2008) developed an excellent set of metrics for classifying 13 types of decision strategies. The metrics operate on the basis of data generated via the Mouselab-type process tracing tool. An advantage of the Mouselab is that it tracks both sequence of information search and time spent on options. The ratio of time spent on options, for example, enables differentiation between the *Dominance/ Majority Strategy* (DOM/MAJ) on one hand and the *Additive/Majority of Confirming Dimensions* (ADD/MCD) types of strategies on the other hand. The Mouselab-generated data however have some limits. They, for example, do not enable discrimination between strategies with identical information search patterns, such as EBA and LEX strategies.

The metrics developed by Riedl, Brandstätter and Roithmayr (2008) assume that a decision-maker applies just one particular strategy. However, in complex choices with high number of options, decision-makers apply two or more different strategies sequentially.

Another method for collecting and analyzing data in complex choices is the Active Information Search (AIS). The AIS is based on a dialogue of a researcher and a participant. Reisen, Hoffrage and Mast (2007) provide detailed comparison of strengths and weaknesses for four process tracing techniques. They note that although the Mouselab is more convenient to use and provides a large amount of data, the AIS has two major advantages over the Mouselab. It can imitate real world data collection better than the Mouselab does. It also does not present options and attributes in a pre-structured manner on the screen, thus, participants are less affected by the experimental setup (Reisen, Hoffrage and Mast, 2007). The AIS, on the other hand, does not allow for some fine-tuned tracking techniques (e.g. recording time spent on attributes and alternatives). Arguably, identification of specific heuristic strategies is more difficult and less precise under the AIS than under Mouselab.

Mouselab-based classification methods implicitly assume that a decision-maker has some understanding of the task and is able to specify his/her goals, preferences and cut-off values for decision attributes. This may not always be the case in complex choices. Information search patterns, for example, may be quite erratic when the decision-maker perceives his/her low expertise in the decision task. In our research, most participants acknowledged their low financial literacy. We also noted a number of inconsistent and/or erratic search patterns. It was difficult to identify single heuristic strategies in such cases.

We considered the above-mentioned limitations in the identification of specific strategies and opted for the classification of two-stage strategies and information search patterns, rather than for the identification of 'pure' heuristics (see Exhibit 1 for examples of information search patterns). We used the method AIS and short verbal protocols to record decision strategies.

Our research intends to add to the growing literature on efficiency of heuristic strategies in complex, high-consequence decisions with multiple options and attributes. We use real-life sets of complex financial products to investigate (a) the types of decision strategies used in complex, high-consequence choices and (b) efficiency of combinations of strategies in terms of quality of choice and information burden.

2. Method

2.1. Participants

The sample involved 220 university undergraduates and post-graduates (115 women and 105 men; average age 27.1 years). The participants self-assessed their financial products knowledge and experience on a scale ranging from zero "no knowledge" to 10 "I am a real financial expert". Sixty-two participants (28.2%) indicated knowledge on levels six to 10 and were considered experts, while the rest (158 participants, 71.8%) indicated knowledge on levels zero to five and were considered non-experts. Twenty-eight out of 115 women and 34 out of 105 men identified themselves as experts. Men accounted for higher levels of perceived expertise in financial products than women (Cramer's V = 0.089, sig. 0.008). Low levels of perceived financial expertise in the sample corresponded with the actual distribution of financial expertise in the total Slovak population (Baláž, 2012; 2014).

2.2. Task

Participants were presented with the following hypothetical task:

"Please imagine you have EUR 10,000. We offer you various types of investments. You can ask for information on eight investment attributes: risk level, annual return, entry fee, optimal investment horizon, condition of access to money (with respect to penalty paid), annual fees, exit fees and names of financial institutions. Please consider the available information and tell us, which product you would invest in."

Investment of EUR 10,000 equalled two annual median net wages in Slovakia in 2013, and simulated a high consequence decision.

Recording sheets included real financial products offered in the Slovak financial market in 2013. In selected cases, we replaced the names of actual financial institutions with invented ones, as to prevent potential impact of the institution's image on investment decision. Range of investments included low-risk products (term deposits in banks and money market funds, essentially 'safe options'), medium risk products (pension funds and investment life insurance policies) and high-risk products (stock market funds). For an example of a complex choice task, see Exhibit 2. Most people are risk averse. Risk aversion may have a significant impact on the choice of a financial product. We selected products with high and low Sharpe ratios in equal proportions for both low-risk and high-risk categories of investment. Product label ('stock fund', 'investment insurance policy') was not necessarily associated with high or low Sharpe ratios.

2.3. Procedure

The research procedure was adapted from a study on complex financial decision-making (Monti et al., 2009). The participants were asked to choose only one financial product. The decision set contained 15 financial products with eight attributes (120 information units in total). The complex choice task condition accounted for a significant burden of information processing. Participants were allowed to request any number and type of information before making their choice. They could request information on any attribute and/or option. They could search information option-wise or attribute-wise, and ask for values of all or just few selected attributes. At the end of each task, participants had to choose one out of 15 financial products. The Trial was repeated four times with different sets of products (Trials 1 to 4). The average task (Trials 1 – 4) took about 1 – 1.5 hours.

Each participant could ask 80 information units as a maximum. Experts asked for less information than non-experts in each of the four Trials, but learning curves were different for these two groups. Amount of the information units requested between Trials 1 and 2 declined from 48.4 vs. 41.2 units for non-experts (Wilcoxon test sig. 0.001) and 45.4 vs. 36.8 units, for experts (sig. 0.066). Between Trials 2 versus the amount of information decreased from 41.2 to 35.6 units for non-experts (sig. 0.002), but only from 36.8 to 35.0 units for experts (sig. 1.000). Finally, amount of information requested between Trials 3 and 4 dropped from 35.6 to 32.7 units for non-experts (sig. 0.021) and 35.0 to 31.5 units for experts (sig. 0.067). Experts seemed to learn most in the early Trials while learning curve for non-experts was more linear. The learning curve also was more linear for the women compared to the men. This is related to higher financial expertise perceived by men compared to women (Baláž, Bačová and Škriniar, 2014).

2.4. Financial Choice Quality Assessment

Optimal or above-average choice is difficult to specify in many multi-attribute choices. The 'best car' or 'best home' are arbitrary concepts and depend on personal preferences over specific decision attributes. In financial choices, 'best investment' is somewhat easier to define. Risk and return are dominant attributes in financial choices, and investors aim at the best ratio between risk and return. The Sharpe Ratio, developed by the Nobel Laureate William Sharpe (Sharpe, 1966), measures the excess return (or risk premium) per unit of deviation in an investment asset: Higher Sharpe ratio means better trade-off between return and risk. Low Sharpe coefficient indicates an investment with relatively low return, but high risk. The 90-day Treasury bill returns are typical measure of risk free return in the USA. Treasury bills were not available in Slovakia, and typical risk-free investment was a term deposit in Slovakia (average return on term deposit was 2.0% p.a. in 2013). Naïve investors often concentrate on risk/return patterns of an asset and disregard investment costs. Each decision set contained 15 products and five classes of investment assets (money market fund, term deposit, stock fund, investment life insurance and pension fund). Each class was represented by three products, but products from the same investment class accounted for different combinations of investment fees. Total return for a particular product was adjusted for entry, annual and exit fees over relevant time period (see Exhibit 2 for details).[3]

2.5. Strategy Identification

We combined information search patterns (established via AIS) and statements in verbal protocols to identify participants' decision strategies. First, we observed how a participant reduced the information burden and narrowed the set of options in stage one.

In stage two, we observed whether a participant asked for all or just some information on attributes of the remaining options. We also took into account statements in short verbal protocols as to establish whether the participant used several attributes to weigh the remaining attribute or whether the choice was made solely on the basis of one attribute.

The efficiency of heuristic strategies was measured via the number of choices of the above-average products (in terms of Sharpe ratio). We also observed whether the absolute value of the Sharpe ratio increased or decreased over time.

[3] Optimal investment horizon, access to money with no penalty and brand were already accounted for in market return. Less known financial institutions, for example, had to offer above-average returns.

3. Results

3.1. Strategies in Stage One

We applied a two-stage analysis to estimate the heuristic strategies. Stage one tracked the strategy the participants used to reduce the information burden in the multi-attribute choice. Three types of reducing strategies were detected:

- *Elimination by aspect* (EBA): Participant asked for information on one or more attributes for all 15 products to eliminate options that do not meet a minimal cut-off value for the most important attribute (Tversky, 1972). The elimination process was sometimes repeated for the second or third most import attribute until the decision set was narrowed to two or more options (e.g. participant no 1 in the attached Exhibit 1). The EBA strategy was used in 37.3% of cases.
- *Recognition heuristic* (REC): Participant asked for information on one or more attributes for selected products only. Some financial products were ignored and no information was sought (e.g. participants no 74, 75 and 187 in Exhibit 1). However, it should be noted that recognition as a reducing strategy in a complex choice may have a different meaning than recognition in a binary choice. 'If one of two objects is recognised and the other is not, then infer that the recognised object has higher value with respect the criterion' (Goldstein and Gigerenzer, 2002). In a complex choice, an option can be ignored *because* it is recognized, deemed unsuitable and excluded from further consideration. Recognition heuristic was used in 45.0% of cases. Frequency of the REC-type strategy increased over Trials 1 – 4, as participants learned to recognize product types.
- *Lexicographic heuristic* (LEX): Participant asked for information on one attribute for all 15 products and then selected the option with the best value on the most important attribute. Lexicographic heuristic was used in 0.7% of cases.

In 16.9% cases there was no reduction of a decision set before the final choice. Participants asked for information on two or more attributes for all 15 products and then selected an option:

- In 6.4% cases participants asked information on all attributes of all 15 products (120 information units) (e.g. participant no 144 in the attached Exhibit 1) so they use the normative strategy.
- In 9.4% cases participants asked information on 2 – 7 attributes of all 15 products (e.g. participant no 7 in the attached Exhibit 1).
- In 1.1% cases participants asked information in option-based search.

3.2. Strategies in Stage Two

The analysis of stage one suggested, which non-compensatory strategy was used to reduce the information burden, eliminate inadequate options and specify a narrow decision set. In stage two we tracked the sequence and amount of information demanded and recorded option-wise, attribute-wise and mixed transitions. We followed Riedl, Brandstätter and Roithmayr (2008) and noted whether a participant applied an attribute-based (AB) or option-based (OB) information search and whether information on all attributes/options was sought or not. We denote search patterns as attribute consistent/attribute selective (AC, AS) and options consistent/selective (OC, OS). Attribute-based searches accounted for a significant majority in stage 2 (91.7%), while the option-based searches were preferred in 8.3% choices.

The participants used a rich repertoire of heuristic strategies. In a total of 880 choices, we detected 37 combinations of stage 1 and stage 2 strategies. Nine combinations (each accounting for at least 20 cases) were generated for 86.9% of all combinations (they are presented in the first column of Table 2).

3.3. Efficiency of Strategies

A heuristic strategy was considered efficient, if the Sharpe ratio of a chosen financial product was higher than the Sharpe ratio of median product in a decision set. There were 15 financial products in a decision set. If a participant chose a financial product with one of seven best Sharpe ratios, the heuristic strategy was considered efficient. A product with the 8th best Sharpe ratio was considered a median choice. Choices of products with 9 – 15 best Sharpe ratios were considered inefficient. Rational and/or knowledgeable investors were expected to choose above-average products (no 1st – 7th best Sharpe ratios).

Above-average products were selected by 148 participants in Trial 1, 143 in Trial 2, 138 in Trial 3 and 129 in Trial 4. Above-average products were chosen in 63.4% out of the 880 total choices (Table 1). Probability of random choice of an above-average product was 7/15 = 46.7%.

T a b l e 1

Quality of Choice: Percentage of Choices of Above-average Products by the Sharpe Ratio

	Total	Experts	Non-experts	Men	Women
Trial 1	67.3	77.4	63.3	66.7	67.8
Trial 2	65.0	61.3	66.5	70.5	60.0
Trial 3	62.7	59.7	63.9	60.0	65.2
Trial 4	58.6	56.5	59.5	60.0	57.4
Total Trials 1 – 4	63.4	63.7	63.3	64.3	62.6

Note: Average choices over all subjects.

Source: Authors‘ calculation.

Numbers of participants who selected above-average products has been decreasing between Trials 1 – 4. However, that does not necessarily mean the quality of choice decreased over time. A participant, for example, chose below-average products in all Trials, but product's Sharpe ratio in Trial 4 (–0.2008) was higher than that in Trial 1 (–0.2217). The worst performing participants improved their choices over time. Some 46.8% of participants chose products with better, 17.3% with the same and 35.9% with worse Sharpe ratios in Trial 4 than in Trial 1.

Table 2 summarizes efficiency of the most frequent heuristic strategies. The table presents only strategies or their combinations with 20+ applications. In the complex financial choices participants selected one from 15 financial products. A random choice would have resulted in the 8th best product. Average product rank (computed via Sharpe ratio) was 6.48. The best results were delivered by the 0-AB, AC, OC (5.95) strategy. The REC-AB, AC, OC (6.27), REC-AB, AS, OS (6.27) and EBA-AB, AS, OS (6.29) performed slightly better than average. Strategies incorporating option-wise search (REC-AB, AS, OB, OS and REC-OB, AS, OS) generated the worst product ranks (7.16 and 8.48).

T a b l e 2

Efficiency of Heuristics in Financial Choice

Strategy type	Frequency	Average Sharpe	Average product rank	Average no of information required
0-AB, AC, OC	6.4%	0.081	5.95	120.00
0-AB, AS, OS	9.4%	0.050	6.67	8.00
EBA-AB, AS, OC	17.2%	0.046	6.63	39.00
EBA-AB, AS, OS	14.0%	0.061	6.29	53.00
REC-AB, AC, OC	5.6%	0.058	6.27	49.00
REC-AB, AS, OB, OS	4.9%	0.026	7.16	16.70
REC-AB, AS, OC	17.2%	0.052	6.36	36.00
REC-AB, AS, OS	8.9%	0.059	6.27	23.82
REC-OB, AS, OS	3.3%	–0.042	8.48	20.62

Note: 0 – no elimination of options in stage 1. Average Sharpe ratio: 0.052. The best Sharpe ratio: 0.313. The worst Sharpe ratio: –0.486. Average product rank: 6.48. Best product rank: 1. Worst product rank: 15.

Source: Authors' calculation.

Information-intensive strategy 0-AB, AC, OC used all 120 information items available in a decision set. The strategy delivered the best results in terms of Sharpe ratio and product rank and was mostly applied by students of informatics. Product rank delivered by this information-intensive strategy (5.95), however, was just slightly better than product rank generated by the REC-AB, AC, OC and REC-AB, AS, OS strategies (6.27). The latter pair of strategies, however, coped with much lower information burden (49.0 and 23.82 information units) than the information-intensive strategy 0-AB, AC, OC.

There was no significant relation between amount of information acquired and quality of choice in terms of Sharpe ratio and product rank. Respective correlation coefficients for 880 choices were 0.070 and –0.055, and were not significant on the 0.01 level.

Participants used only some 39.7 information units in their choices, out of total 120 available units per each decision set.

3.4. Gender and Expertise Differences

The t-test indicated no gender differences in selecting a financial product with better Sharpe ratio and/or product rank. The t-test indicated that the experts were rather more likely to pick products with higher Sharpe ratio and/or product rank, but the difference was not significant on the 0.05 level. Experts were more likely to apply compensatory strategies generating best product ranks (0-AB, AC, OC and the REC-AB, AC, OC) than non-experts, but the differences were not significant on the 0.05 levels (approximate significance levels for the Cramer's V test were 0.286 and 0.333 respectively).

The perceived expertise in financial products was reflected in a higher representation of the REC strategy in stage one. In stage one the experts chose the REC strategy in 58.9%, while the non-experts in 40.05 cases. The difference was significant on the 0.000 level (Cramer's V = 0.170).

3.5. Consistency of Strategies Used

Each complex choice included four variants of the same task. Did the participant use the same combination of strategies in solving the variants of the same task?

- Repeated use of the same introductory (stage 1) strategy (0, EBA, REC) was seen in 64.1% of cases. Consistent use of the same introductory strategy increased over Trials from 74.4% between Trials 2 and 1 to 91.4% between Trials 4 and 3.
- Similar pattern was observed for the use of complete (combined) strategies. Some 48.6% of participants used the same combination of strategies between Trials 2 and 1, but 63.6% between Trials 4 and 3. Some 26.2% of participants used the same combinations of strategies in all four Trials.

A typical pattern of the complex financial choice was re-using of the same strategy, possibly with small variation of strategies (Table 3). Increasing consistency of strategies between Trials may indicate that participants opted for fine-tuning their decision procedures, rather than changing them.

Table 3

Internal Consistency of Strategies in Complex Financial Choice

	Consistency in introductory strategy (N = 220 x 3)	**Consistency in combined strategy (N = 220 x 3)**
Match between Trial 2 and Trial 1	74.4%	48.6%
Match between Trial 3 and Trial 2	83.6%	55.5%
Match between Trial 4 and Trial 3	91.4%	63.6%
Match in all Trials 1 – 4	64.1%	26.2%

Source: Authors' calculation.

Was it better to change the strategy or to stick to the same one? Most changes in the use of combined strategies happened between Trials 1 and 2. Participants who modified their strategy between Trials 1 and 2 were more likely to achieve an increase in the Sharpe ratio than participants sticking to the same strategy (Table 4). Participants who modified their strategy between Trials 4 and 3, however, were worse off than those who continued to use Trial 3 strategy. It follows that modification of a decision strategy worked better at the beginning of the learning curve than at its end. This finding seems to corroborate the conceptual framework of an adaptive decision maker by Payne, Bettman, and Johnson (1993). The effects of consistent/inconsistent use of decision strategies, however, were moderate (see respective Cramer's V under the Table 4).

Table 4

Crosstab for Internal Consistency of Combined Strategies and Change in Sharpe Ratio

		Change in value of Sharpe ratio			
		Decrease	*No change*	*Increase*	Total
Match between Trial 2 and Trial 1 [(a)]	no	16.8%	8.6%	25.9%	51.4%
	yes	18.2%	10.9%	19.5%	48.6%
Match between Trial 3 and Trial 2 [(b)]	no	20.0%	6.4%	18.2%	44.5%
	yes	28.6%	13.2%	13.6%	55.5%
Match between Trial 4 and Trial 3 [(c)]	no	15.0%	7.7%	13.6%	36.4%
	yes	18.6%	14.1%	30.9%	63.6%

Note: (a) Cramer's V = 0.107, Sig. = 0.287; (b) Cramer's V = 0.185, Sig. = 0.023; (a) Cramer's V = 0.128, Sig. = 0.166;

Source: Authors‘ calculation.

4. Discussion

We were interested in what strategies individual investors use in the process of choosing a financial product and how effective these strategies and their combinations were. We confirmed previous findings that choices developed in two stages. Stage one employed non-compensatory strategies for reduction of information burden, elimination of inadequate options and specification of a more narrow decision set. Three main types of reduction strategies were detected in stage one: EBA, REC and LEX. No reductions were noted in 16.9% of participants. Attribute-based searches accounted for significant majority in stage 2 (91.7%), while the option-based searches were preferred in 8.3% of choices.

The research also confirmed that combinations of decision strategies, rather than single heuristics, were applied in complex financial choices. In a total of 880 choices, we detected 37 combinations of stage 1 and stage 2 strategies. Nine combinations generated 86.9% of all combinations.

Naïve decision strategies worked quite well in choice of financial products. Average Sharpe ratios and product ranks were higher than random choices of financial products. Above-average products were chosen in 63.4% out of 880 total choices. Probability of random choice of an above-average product was 7/15 = 46.7%.

The normative strategy has proven to be most effective in complex financial choices, however, at the cost of high effort required. Strategies incorporating option-wise search generated the worst product ranks.

Economic theories of utility maximization (von Neumann and Morgenstern, 1944) involve a number of simplifying assumptions on information processing: (1) that individuals have all the available information for decision making; (2) that individuals have unlimited processing capacity; (3) that all attribute values and decision weights are known; and (4) that individuals use optimal analytical methods to make decisions. Accepting utility maximization framework and measuring efficiency of investment choice by Sharpe ratio is based on some strong assumptions concerning decision-makers:

- know typical risk/return indicators for particular classes of investment product;
- are able to deduct investment costs (total expense ratios) from returns and compute net present values of long-term investments;
- understand and accept that in the long-term risky products deliver higher returns than low-risk investments.

These assumptions are hardly realistic. Vast majority of investors, including our participants, consider limited amount of information on risk and returns, which turned out to be the dominant attributes in all choices. Few investors are able to compute total expense ratios, and compare compound costs to compound returns. They seem to prefer to apply linear approximations of risks, returns and investment costs.

We found out that heuristic decision strategies were not strong enough to select optimal financial products, but operated surprisingly well in terms of the amount of (limited) financial knowledge and cognitive effort applied by our participants. It seems that in the task of financial decisions the strong dominant attributes (return, cost and inferred risk) allow for making good choices even in conditions of very complex information.

We found no significant relation between quality of choice in terms of Sharpe ratio/product rank on one hand, and (a) amount of information acquired; (b) gender and perceived financial expertise of participant, on the other hand. This finding corresponds with the experimental study of Ackert, Bryan and Tkac (2010) on predicting mutual fund performance. Students of different courses of the

Georgia Tech University and employees of the Federal Reserve Bank of Atlanta used ‘good feature’ heuristic to pick mutual fund with best performance. Over 60% of participants used this heuristic often, independently of the relative amounts of prior financial training and self-reported expertise (Ackert, Bryan and Tkac, 2010, p. 146). The abovementioned authors also found no significant difference in subjects’ performance in the prediction of comparative mutual fund performance differs across groups of participants with different levels of financial training and expertise.

Our participants made trade-offs between accuracy and amount of cognitive effort of heuristic strategies. Some participants used the same strategies and some modified them across the repeated Trials in complex financial choices. Modification of decision strategy worked better at the beginning of the learning curve than at its end. This finding seems to corroborate the conceptual framework of an adaptive decision maker by Payne, Bettman and Johnson (1993).

Participants coped with significant information burden. Only a few of them chose the normative compensatory strategy, which provided the best choice. Far more decision-makers made compromise between decision accuracy and minimizing their cognitive effort. Nevertheless, the choices of a financial product made by participants were better than random choices. Heuristic decision strategies operated well in terms of limited financial knowledge by most participants.

This paper, like many studies in the behavioural economics, has some limitation. The research targeted population of the Slovak University students. We make no claims on representativeness of the sample for total Slovak population.

One limitation of our study applies to the use of AIS. The AIS is able to imitate the real-world environment of information acquisition. The price to pay is that AIS does not allow for precise identification of particular heuristics. Vast majority of heuristic strategies was attribute-based and involved compensatory weighting. We suspect that 0-AB, AC, OC, and REC-AB, AC, OC and REC-AB, AC, OC-type strategies are identical with the Majority Strategy. The MAJ-type strategies operated well in a complex financial choice. The option based strategies (REC-OB, AS, OS, and final phase of the REC-AB, AS, OB, OS) are likely SAT and DIS-type heuristics. These option-based strategies underperformed in a financial choice. These findings may indicate the importance of attribute-based compensatory strategies in complex financial choices. There is an option to repeat the experiment with two sets of participants. One set may collect information via the AIS while the second one via the Mouselab method. Comparison of two sets may indicate (a) how different modes of information access impact acquisition of information and (b) the precise types of heuristic strategies applied in complex financial choices.

Experts and non-experts did not differ in quality of their choices when using heuristic strategies. This finding has some limitations as well. No participant tried to compute the effect of investment costs on total return during the research task. In further research, experts can be encouraged to use expert methods for selecting financial products. Choices based on the expert methods can be compared to those achieved via naïve strategies.

Experiments with complex decisions can be extended to other high-consequence choices, such as purchase of a home or selection of a medical plan. Where values of objects are arbitrary, optimal or satisfying solution can firstly be identified via mathematical methods, such as the analytical hierarchy process (Saaty, 1980), data envelopment analysis (Charnes, Cooper and Rhodes, 1978) and/or TOPSIS (Hwang and Yoon, 1981), and secondly compared with the results of naïve decision strategies.

References

ACKERT, L. F. – BRYAN, K. C. – TKAC, P. A. (2010): An Experimental Examination of Heuristic-Based Decision Making in a Financial Setting. Journal of Behavioral Finance, *11*, No. 3, pp. 135 – 149.

ABALUCK, J. – GRUBER, J. (2011): Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D program. American Economic Review, *101*, No. 4, pp. 1180 – 1210.

ANDERSSON, A. – RAKOW, T. (2007): Now You See It Now You Don't: The Effectiveness of the Recognition Heuristic for Selecting Stocks. Judgment and Decision Making, *2*, No. 1, pp. 29 – 39.

BALÁŽ, V. (2012): Pociťovaná a skutočná finančná gramotnosť. Ekonomický časopis/Journal of Economics, *60*, No. 7, pp. 681 – 697.

BALÁŽ, V. (2014): Komplexné voľby. Bratislava: VEDA, vydavateľstvo SAV.

BALÁŽ, V. – BAČOVÁ, V. – ŠKRINIAR, P. (2014): Experience, Gender and Information Search Patterns in Complex Economic Decision Making. Studia Psychologica, *56*, No. 1, pp. 3 – 20.

BETTMAN, J. R. – LUCE, M. F. – PAYNE, J. W. (1998): Constructive Consumer Choice Processes. Journal of Consumer Research, *25*, No. 3, pp. 187 – 217.

BORGES, B. – GOLDSTEIN, D. G. – ORTMANN, A. – GIGERENZER, G. (1999): Can Ignorance Beat the Stock Market? Chapter 3. In: GIGERENZER, G. and TODD, P. M. (eds): Simple Heuristics That Make us Smart. New York: Oxford University Press, pp. 55 – 72.

BOYD, M. (2001): On Ignorance, Intuition, and Investing: A Bear Market Test of the Recognition Heuristic. Journal of Psychology and Financial Markets, *2*, No. 3, pp. 150 – 156.

CHARNES, A. – COOPER, W. W. – RHODES, E. (1978): Measuring the Efficiency of Decision-making Units. European Journal of Operational Research, *2*, No. 6, pp. 429 – 444.

DeMIGUEL, V. – GARLAPPI, L. – UPPAL, R. (2009): Optimal versus Naive Diversification: How Inefficient is the 1/N Portfolio Strategy? Review of Financial Studies, *22*, No. 5, pp. 1915 – 1953.

FISHBURN, P. C. (1974): Lexicographic Orders, Utilities and Decision Rules: A survey. Management Science, *20*, No. 11, pp. 1442 – 1471.

GÄRLING, T. – KIRCHLER, E. – LEWIS, A. – Van RAAIJ, F. (2009): Psychology, Financial Decision Making, and Financial Crises. Psychological Science in the Public Interest, *10*, No. 1, pp. 1 – 47.

GIGERENZER, G. – TODD, P. M. – the ABC Research Group (1999): Simple Heuristics That Make Us Smart. New York: Oxford University Press.

GOLDSTEIN, D. G. – GIGERENZER, G. (2002): Models of Ecological Rationality: The Recognition Heuristic. Psychological Review, *109*, No. 1, pp. 75 – 90.

HWANG, C. L. – YOON, P. K. (1981): Multiple Attribute Decision Making Methods and Applications. Berlin: Springer-Verlag.

IYENGAR, S. S. – KAMENICA, E. (2010): Choice Proliferation, Simplicity Seeking, and Asset Allocation. Journal of Public Economics, *94*, No. 7 – 8, pp. 530 – 539.

KEENEY, R. L. – RAIFFA, H. (1976): Decisions with Multiple Objects: Preferences and Value Tradeoffs. New York: Wiley.

KIDA, T. – MORENO, K. K. – SMITH, J. F. (2010): Investment Decision Making: Do Experienced Decision Makers Fall Prey to the Paradox of Choice. Journal of Behavioral Finance, *11*, No. 1, pp. 21 – 30.

MONTI, M. – BERG, N. – GIGERENZER, G. – MARTIGNON, L. (2009): The Impact of Simplicity on Financial Decision-making. Proceedings of the 31st Annual Conference of the Cognitive Science Society, *386*, No. 01/2009, pp. 1846 – 1851.

von NEUMANN, J. – MORGENSTERN, O. (1944): Theory of Games and Economic Behavior. Princeton: Princeton University Press.

PAYNE, J. W. (1976): Task Complexity and Contingent Processing in Decision Making: An Information Search and Protocol Analysis. Organizational Behavior and Human Performance, *16*, No. 2, pp. 366 – 387.

PAYNE, J. W. – BETTMAN, J. R. – JOHNSON, E. J. (1993): The Adaptive Decision Maker. New York: Cambridge University Press.

REISEN, N. – HOFFRAGE, U. – MAST, F. W. (2007): Identifying Decision Strategies in a Consumer Choice Situation. Judgment and Decision Making, *3*, No. 8, pp. 641 – 658.

RIEDL, R. – BRANDSTÄTTER, E. – ROITHMAYR, F. (2008): Identifying Decision Strategies: A Process and Outcome-based Classification Method. Behavior Research Methods, *40*, No. 3, pp. 795 – 807.

RUSSO, J. E. – DOSHER, B. A. (1983): Strategies for Multiattribute Binary Choice. Journal of Experimental Psychology: Learning, Memory, and Cognition, *9*, No. 4, pp. 676 – 696.

SAATY, T. L. (1980): The Analytic Hierarchy Process. New York: McGraw Hill.

SEN, A. K. (1966): A Possibility Theorem on Majority Decisions. Econometrica, *34*, No. 2, pp. 491 – 499.

SHAH, A. K. – OPPENHEIMER, D. M. (2008): Heuristics Made Easy: An Effort-reduction Framework. Psychological Bulletin, *134*, No. 2, pp. 207 – 222.

SHARPE, W. (1966): Mutual Fund Performance. Journal of Business, *39*, S1, pp. 119 – 138.

TVERSKY, A. (1969): Intransitivity of Preferences. Psychological Review, *76*, No. 1, pp. 31 – 48.

TVERSKY, A. (1972): Elimination by Aspects: A Theory of Choice. Psychological Review, *79*, No. 4, pp. 281 – 299.

E x h i b i t 1: **Heuristics in Complex Choices**

Participant no 1: EBA-AB, AS, OS

Trial 1	Risk	Return	Entry fee	Investment horizon	Accessibility of savings	Regular fees	Exit fee	Brand
MMF 1		1						
MMF 2	2	1		3				
MMF3	2	1		3				
TD 1	2	1		3				
TD 2	2	1	8	3				
TD 3	2	1	8	3				
SF 1	2	1		3				
SF 2	2	1		3				
SF 3	2	1		3				
IIP 1	2	1		3				
IIP 2	2	1	7	3	4	6	5	
IIP 3	2	1	7	3	4	6	5	
PF 1	2	1		3				
PF 2	2	1		3				
PF 3	2	1		3				

Participant no 7: 0-AB, AS, OC

Trial 1	Risk	Return	Entry fee	Investment horizon	Accessibility of savings	Regular fees	Exit fee	Brand
MMF 1	2	1	3			5	4	
MMF 2	2	1	3			5	4	
MMF3	2	1	3			5	4	
TD 1	2	1	3			5	4	
TD 2	2	1	3			5	4	
TD 3	2	1	3			5	4	
SF 1	2	1	3			5	4	
SF 2	2	1	3			5	4	
SF 3	2	1	3			5	4	
IIP 1	2	1	3			5	4	
IIP 2	2	1	3			5	4	
IIP 3	2	1	3			5	4	
PF 1	2	1	3			5	4	
PF 2	2	1	3			5	4	
PF 3	2	1	3			5	4	

Participant no 74: REC-AB, AS, OC

Trial 1	Risk	Return	Entry fee	Investment horizon	Accessibility of savings	Regular fees	Exit fee	Brand
MMF 1	2	1						
MMF 2	2	1						
MMF3	2	1						
TD 1	2	1	4	6		3	5	
TD 2	2	1	4	6		3	5	
TD 3	2	1	4	6		3	5	
SF 1	2	1	4	6		3	5	
SF 2	2	1	4	6		3	5	
SF 3	2	1	4	6		3	5	
IIP 1								
IIP 2								
IIP 3								
PF 1								
PF 2								
PF 3								

Participant no 75: REC-AB, AC, OC

Trial 2	Risk	Return	Entry fee	Investment horizon	Accessibility of savings	Regular fees	Exit fee	Brand
MMF 1	7	6	2	3	1	5	4	8
MMF 2	7	6	2	3	1	5	4	8
MMF3	7	6	2	3	1	5	4	8
TD 1								
TD 2								
TD 3								
SF 1								
SF 2								
SF 3								
IIP 1								
IIP 2								
IIP 3								
PF 1								
PF 2								
PF 3								

Participant no 144: 0-AB, AC, OC

Trial 1	Risk	Return	Entry fee	Investment horizon	Accessibility of savings	Regular fees	Exit fee	Brand
MMF 1	2	1	4	6	7	3	5	8
MMF 2	2	1	4	6	7	3	5	8
MMF3	2	1	4	6	7	3	5	8
TD 1	2	1	4	6	7	3	5	8
TD 2	2	1	4	6	7	3	5	8
TD 3	2	1	4	6	7	3	5	8
SF 1	2	1	4	6	7	3	5	8
SF 2	2	1	4	6	7	3	5	8
SF 3	2	1	4	6	7	3	5	8
IIP 1	2	1	4	6	7	3	5	8
IIP 2	2	1	4	6	7	3	5	8
IIP 3	2	1	4	6	7	3	5	8
PF 1	2	1	4	6	7	3	5	8
PF 2	2	1	4	6	7	3	5	8
PF 3	2	1	4	6	7	3	5	8

Participant no 187: REC-OB, AS, OS

Trial 1	Risk	Return	Entry fee	Investment horizon	Accessibility of savings	Regular fees	Exit fee	Brand
MMF 1								
MMF 2								
MMF3	5	1	3		2		4	
TD 1								
TD 2								
TD 3								
SF 1								
SF 2	7	6		9	8			
SF 3								
IIP 1	11	10			12	13		
IIP 2								
IIP 3								
PF 1								
PF 2								
PF 3	15	14			16	17		

Notes: MMF – money market fund; TD – term deposit; SF – stock fund; IIP – investment insurance policy; PF – pension fund.
Source: Author's calculation.

E x h i b i t 2: **Example of Complex Choice: Unlimited Access to Information**

	Product	**Risk**	**Return**	**Entry fee**	**Optimal time horizon**	**Access to money with no penalty**	**Annual fee**	**Exit fee**	**Brand**
A	Money market fund 1	very low	comparable to TD	0.20%	in 1 year	in 1 week	0.10%	nil	Slovenská sporiteľňa
B	Money market fund 2	very low	comparable to TD	0.10%	in 1 year	in 10 days	0.20%	nil	OTP banka
C	Money market fund 3	very low	comparable to TD	0.00%	in 1 year	in 1 week	0.10%	nil	Zuneda
D	Term deposit 1	none	current yield on TD	0.00%	in 1 year	after 1 year	0.00%	nil	VÚB banka
E	Term deposit 2	none	current yield on TD +0.2%	0.00%	in 1 year	after 1 year	0.00%	nil	Dexia
F	Term deposit 3	none	Current yield on TD +0.4%	0.00%	in 1 year	after 1 year	0.00%	nil	Zuneda
G	Stock fund 1	high, potential loss up to 35%	2 - 4 times return on TD	2.50%	over 10 years	in 10 days	2.50%	1.00%	IAD Investments
H	Stock fund 2	high, potential loss up to 25%	2 - 5 times return on TD	2.00%	over 10 years	in 1 week	1.20%	nil	DeliaCagnotte
I	Stock fund 3	high, potential loss up to 35%	3 – 6 times return on TD	3.00%	over 10 years	in 1 week	2.30%	2.00%	VÚB banka
J	Investment life insurance 1	low, moderate but sure return	comparable to TD + 1.5%	3.50%	min. 10 years	after 2 years	4.00%	nil	Habitatpro
K	Investment life insurance 2	medium, no return guaran-teed	comparable to TD + 4.0%	4.90%	min. 10 years	after 2 years	5.00%	nil	Kooperativa
L	Investment life insurance 3	medium/low, low return possible	comparable to TD + 3.1%	4.40%	min. 10 years	after 2 years	4.70%	nil	Victoria Volksbank
M	Pension fund 1	medium, no return guaran-teed	as in TD + 1.3%	0.00%	min. 15 years	after 10 years	1.95%	nil	ING Sympatia
N	Pension fund 2	medium/low, low or no return possible	comparable to TD + 1.8%	0.00%	min. 15 years	after 10 years	1.80%	1.00%	AXA
O	Pension fund 3	medium, no return guaran-teed	comparable to TD + 2.5%	0.00%	min. 15 years	after 10 years	1.00%	nil	Pontilia Fortexa

Notes: TD – term deposit in bank.

Source: Author’s calculation.