ETHICS AND FINANCE

Collective Risk Assessment

Collective Risk Assessment

How Swarm Intelligence Could Revolutionise Traditional Approaches to Financial Risk Assessment

Andreas Bauer, Julian Gropp, and Tobias Weinmann

Keywords

Risk Assessment, Swarm Intelligence, Expert Judgement, Behavioural Finance

In recent years, traditional risk assessment has come more and more under fire. The judgement of experts in combination with statistical and historical data was often perceived as an objective measure and prediction of risk. However, these orthodox assumptions seem to be counterbalanced by empirical evidence. Yet findings in the fields of swarm intelligence and behavioural finance seem to lead to promising alternatives. This paper argues for an investment tool that is based precisely on these findings and thus could help reduce risk and enhance experts' judgements.

andreas.eelco@gmail.com
jfb.gropp@gmail.com
tobias.weinmann@gmail.com

1. Introduction

In recent years, traditional risk assessment has come more and more under fire. The judgment of an expert in combination with statistical and historical data is often perceived as an objective measure and prediction of risk. Especially in the financial sector, the role of risk assessment in structuring information and quantifying uncertainty has increased steadily over the last decades. Risk assessments are normally understood as "structured methods for identifying, analysing and evaluating risks, which provide useful support in the decision making and the regulatory processes" (Skjong/Wentworth 2001: 537). Hereby, experts' judgements are assigned an essential position in the procedure of hazard identification and risk estimation. However, experts' judgement has often been accepted as an objective estimation of risk, an assumption that empirical evidence does not support.

To shed light on the various problems of risk assessment and experts' judgement, this paper first provides a condensed overview of the origin of mathematical perception of risk in the financial sector. That is to say, Harry Markowitz's "Portfolio Selection" is presented as the first investment model that applies proper risk assessment procedures. Here, risk is based on statistical and historical data. However, especially during a crisis, the basic assumptions of the Modern Portfolio Theory (MPT) seem to waiver. As a next step, general suppositions of behavioural finance and collective intelligence are introduced as an alternative access to risk assessment in the financial sector. Hence, the rational, statistical approach of Markowitz and the irrational, but often correct decision-making of the crowd are to be confronted. Finally, the results are used to develop a conceptual investment tool for a company in the financial sector, preferably a bank. This tool suggests that these companies could benefit from the predictions of laymen, in contradistinction to predictions from experts. That is, we will discuss how to apply these theories to a tool, making investment decisions easier using the results of a probabilistic forecasting method. To achieve this goal, behavioural finance theories and studies on prediction markets and on the ability of laymen to make predictions on stock market prices will be considered. These concepts will deliver a basis for further studies and experiments, and the additional empirical evidence thereby gained will lead to a mechanism for a tool which is capable of improving and enhancing investment decisions according to our thesis.

2. *Modern Portfolio Theory and its Assumptions*

2.1 Portfolio Selection

The financial crisis of 2008 harshly revealed the deficiency of the Modern Portfolio Theory (MPT), namely the Portfolio Selection that was introduced by Harry Markowitz in 1952. Although criticism accelerated after the weaknesses became obvious, Markowitz's model and especially its later modifications by James Tobin and William Sharpe are still predominately used in the banking and investment sector all around the world.

The pivotal sentences in the introduction of Markowitz's Portfolio Selection that was published in the Journal of Finance, sound nowadays very familiar, but were at that time nothing short of groundbreaking:

> "We first consider the rule that the investor does (or should) maximize discounted expected, or anticipated, returns. This rule is rejected both as a hypothesis to explain, and as a maximum to guide investment behavior" (Markowitz 1952: 77).

Hence, Markowitz calls into question the thitherto-accepted theory of an investor who buys the share with the highest expected value at the best price.

> "We next consider the rule that the investor does (or should) consider expected return a desirable thing and variance of return an undesirable thing" (ibid.).

The following line of mathematical argumentation appears very elegant and coherent. (1) The desired output from an investor's portfolio is a high return, while the "costs" to be minimised is the risk of that return. Here, risk is measured by standard deviation, whereas returns are measured by averaging returns over a specified past period. (2) A diversified portfolio on the Efficient Frontier offers a lower volatility and a higher return than the best singular share, as long as shares are not correlated. Thus, an investor would prefer an efficient portfolio to a singular share. (3) A portfolio is called efficient if and only if there is no other portfolio which attains the same expected return while having a lower volatility and respectively attains a higher expected return while having the same volatility. (4) The sum of all possible efficient portfolios can then be calculated and a rational investor would choose the one that best suits his profit expectations and readiness to assume risk.

Naturally, the selection of an efficient portfolio is based on certain explicit and implicit assumptions. These are subdivided into characteristics of investors and features of the market (cf. Wagemann 2009: 20; Auckenthaler 1994: 154). Characteristics of investors include the pre-supposition that investors are rational and risk-averse, meaning investors prefer a portfolio with a lower risk to a portfolio with a higher risk under the condition that they both attain the same expected return. Moreover, all investors aim to maximise economic utility and are interested in the expected value and variance in order to optimize their portfolio. Thus, efficient portfolios can only be construed if and only if the expected value, the variance, and the covariance can be included in the portfolio analysis. The features of the market, on the other hand, can be summarised in four assumptions.

First, the market has to be frictionless, a theoretical trading environment where all costs and restrictions associated with transactions are non-existent. A further meaning in the context of the Portfolio Theory is the fact that assets can be divided into parcels of any size and that these parcels can be purchased on the free market. Second, complete competition is presumed. Hence, the access to the investor market is not subject to restrictions and therefore arbitrage opportunities are eliminated. From a complete competition on the market, Markowitz also follows the Gaussian distribution for asset returns. Third, short sales are excluded and capital is completely invested. Finally, the portfolio must not contain assets with a correlation coefficient of -1, and a risk-free asset with a variance of 0.

2.2 Critique of the MPT

Obviously, the assumptions of the MPT have to be assessed critically, especially from a post-financial-crisis perspective. Actually, Markowitz himself addresses a crucial issue by formulating a provocative rhetorical question in the context of the financial crisis of 2008.

> "'You, Harry Markowitz, brought math into the investment process with your 1952 article and 1959 book. It is fancy math that brought on this crisis. What makes you think now that you can solve it?'" (Markowitz 2008).

The mathematician Benoit Mandelbrot and the journalist Richard L. Hudson criticise precisely this "fancy math" used by Markowitz. In their opinion, the assumptions, which the orthodox financial theory is based on, seem to waver when confronted with empirical evidence. In fact, the movements on the financial markets do not seem to correspond to normal, distributed occurrences. Hence, financial markets are far more risky than the advocates of the MPT would like to admit. But since the normal distribution of returns is presented as a pivotal presupposition within the MPT, the mean-variance optimisation has to be scrutinised critically (cf. Mandelbrot/Hudson 2004).

Moreover, it seems as if the market does not cooperate with the assumption that past performance is indicative for future performance. Financial markets do not seem to have the characteristics of a slowly moving river. On the contrary, market prices seem to jump and twitch, and because they are so volatile, the better part of market price movements seem to occur in a very short period of time. Markowitz's approach to investing has been criticised from a mathematical-empirical standpoint. In order to reduce risk in a portfolio, Markowitz argues that it would be crucial to own securities that do not have the same price movements, meaning if one component of the portfolio was moving downwards, an investor would want to own assets that move in the opposite direction. In other words, various components of the portfolio should not be correlated or even in some cases should be negatively correlated. However, evidently positive correlations between various asset classes increase more and more. The European standard index for assets Euro Stoxx 50 and the American S&P 500, for example, have in 80% of the cases steady development nowadays. This is a development that has evolved over the last 10 to 15 years (cf. Rottwilm 2008). Not only do assets appear to have the same price movements, but real estates, private equity, and hedge funds also have the tendency to move in the same direction. It could be argued that globalisation has finally reached the investor market and has torn down the separating barriers between various asset classes. But however one wants to construe causal reasons for positive correlations, we first and foremost have come to the conclusion that the assumption of no or negative correlations between assets is contradicted by empirical evidence. Nowadays, most asset classes display a positive correlation, especially during a crisis. Thus, today the MPT does not efficiently achieve its main task: reducing risk.

Another great criticism of the MPT relates to the assumption that investors are rational and risk-averse. In the bubble markets of the 1990s and of today, investors have shown remarkable and consistent behaviour in ignoring risk. Especially the theory of behavioural finance contradicts the model of a rational human being.

3. *Behavioural Finance and Swarm Intelligence*

3.1 Behavioural Finance

As a discipline, behavioural finance tries to explain financial phenomena by assuming that agents are not rational or only semi-rational. Although an inherent and accepted framework, such as the Homo economicus, does not exist in behavioural finance, the following framework provides an overview of the field. Financial decision makers' preferences tend to be multifaceted, open to change and often formed during the decision process itself. Agents are satisfiers and not optimisers; this means that agents do not optimise their market of goods but satisfy their needs (cf. Simon 1956). They are adaptive in the sense that the nature of the decision and environment within which it is made influence the type of the process utilised. Decision makers are neurologically predisposed to incorporate affect (emotion) into the decision process (cf. Razek 2011).

Behavioural finance has made great attempts to understand the psychology of the decision-making process. For the portfolio design, expectations of future revenues have to be formed. Traditional finance acts on the assumption of complete information. Hence, agents have enough knowledge to predict the future. In reality, this is not possible. Expectations are formed by beliefs. How beliefs are formed in practice has been examined by psychologists who have identified several cognitive biases.

Firstly, agents are not risk-neutral. They tend to be risk-averse and risk-loving at the same time. Instead of managing one portfolio, many people make separate mental accounts. These mental accounts are managed by different strategies. While being risk-averse during the conclusion of an insurance policy, the same agents love risk when gambling. Money is treated separately from other parts of wealth during gambles or similar events (cf. Barberis/Huang 2001). Generally, agents have the tendency to overestimate their predictions for success and their own skills. Experts are especially afflicted by this bias. For example, when asking for the level of the Dow Jones Index in a year, the 98% confidence intervals only include the actual value in 60% of the time. There are also certainty banks, which means that certain perceived events occur less often (~80%) and impossible perceived events occur more often (~20%) than people think (cf. Barberis/Thaler 2003).

If people face conflicting beliefs, they will feel anxiety and internal tension. Thus individuals try to reduce inner tension by either changing past feelings, opinions, and beliefs or by rationalising choices afterwards. This effect is called cognitive dissonance. Research has shown that investors hold on to bad investments to avoid admitting they made bad decisions (cf. Ricciardi/Simon 2000). When estimating the probability of an event, for example being mugged, people search their memory for information or events. Although the method itself is reasonable, it can provide incorrect results, because not all memories are equally retrievable. The mugging of a close friend would weigh more heavily and falsify estimations. This effect is known as availability (cf. Barberis/Thaler 2003).

Estimates are often made by anchoring and adjustment. Agents start with an initial value (anchor) and adjust it to their final result. The context of the estimations can provide the anchor or it can be a result of a partial computation. But however the initial value is generated, the adjustments to it are insufficient (cf. Razek 2011). In an experiment, groups have been asked to estimate how many citizens of the U.S. being Afro-American. One group was asked to compare their estimation with 10%, the other with 60%. The first group estimated 25%, the second 45% (cf. Barberis/Thaler 2003). Especially complex systems, which can change abruptly even due to small influences, are estimated wrongly because of anchoring and adjustment.

Although economists argue that people learn to avoid biases, experts make fewer mistakes and incentives dispose of these effects, empirical evidence shows that this is not the case. Biases are attenuated by prior factors but cannot be avoided entirely. Together with the problems of the MPT presented earlier in the paper, the cognitive biases and the irrationality of agents create doubt in an effective investment process. The assessment of risk, in particular, is an emerging problem in a more complex world. The field of swarm intelligence has shown promising approaches in making accurate estimations and predictions and hence could solve problems for the investment sector.

3.2 Swarm Intelligence

Swarm intelligence comes into existence when a group solves a problem as a collective, which no part of the group could have solved alone (cf. Fischer 2010: 23). To solve a complex problem as a group, it is not necessary that its individuals are very smart, informed or centrally organised. Ants or bees, for example, are very efficient foragers, although they lack the overview and capabilities to find and forage food sources or to determine good nests on their own. Humans also use swarm intelligence. Online platforms like Youtube or digg.com utilise the wisdom of the crowd to find interesting videos or news by applying voting mechanisms. For investments, the estimations of risk and revenue are crucial. Research has shown the greatest performance of estimations by crowds.

One simple way to understand swarm-based estimations is the so-called estimation of oxen. The underlying experiment is a carnival game that was observed by Francis Galton in 1906. Participants were asked to estimate the weight of an ox. About 800 fairgoers participated in the game. Galton later bought all tickets from the fair and plotted them. All guesses ranged from 1,074 to 1,293 pounds and the mean amounted to 1,197 lbs. Actually, the ox weighed 1,198 pounds, hence the mean only deviated by one pound. As long as estimations are independent, experiments show that the mean of a group is more accurate than its participants. One of the reasons for this phenomenon is explained by Scott Page's diversity law:

collective error = average individual error – diversity (deviation) of estimations

The collective error is the difference between the average of all estimations and the actual out-come. The average individual error is the average deviation of every single estimation from the actual outcome. According to Page's law, the collective error has to be less than the individual error because of the diversity of estimations (cf. Fischer 2010: 82 ff.).

Another swarm phenomena can be examined at the game show "Who Wants to Be a Millionaire?". When the audience is asked a question, it is right 90% of the time, while experts (phone jokers) are only correct 66% of the time. Condorcet, a French mathematician and democrat who lived during the American Revolution, tried to prove that the majority of a group was more likely to make the right choice than one individual on his own. His jury theorem proves his idea under some assumptions, most importantly that the members of the group are more likely to make the right rather than the wrong choice. Under this assumption, the probability for the majority to make the right choice rises with its members. Even if parts of a group are only as good as a coin or a dice, the jury theorem is still correct, but the variance of the results rises. (cf. Fischer 2010: 87 ff.) By using the swarm intelligence phenomena, a group can make the best of cognitive biases and make good estimations. Availability of information cancels itself out in a group, as different people have different memories. On the other hand, collective memories, like 9/11, will still affect whole groups. Mental accounting does not have an impact on groups, as the different risk-averse and risk-loving accounts can balance each other. However, the way questions are posed would have a strong impact. This is also true for anchoring and adjustment. If the question already imposes a frame, the estimations will be similar. Overconfidence problems can be averted because the confidence of participants' estimations does not have to be used for swarm-generated data. Even if the confidence, for example in prediction markets, is part of the generated data, the different participants will balance each other out as they are all overconfident. In general, swarm intelligence allows the participants to be irrational and make mistakes, but the whole crowd's output is rational and correct or at least probably correct. But frames can impose irrational individual behaviour that does not cancel itself out. Therefore a tool needs a diverse – especially a cognitively diverse – group and rules to work properly. A group should have five diversity characteristics (cf. Fischer 2010; Page 2007):

1. A great diversity of relevant fields of knowledge
2. Different perspectives or diverse ways of representing situations and problems
3. Perspectives have to be categorised and interpreted diversely by the group
4. Members need to alter in their heuristics, meaning they need different problem-solving strategies
5. There have to be diverse ways of inferring cause and effect

Moreover, every individual in the group has to make its decisions and estimations independently and separately. They have to be objective or not directly affected by their answer, and everyone has to answer the same question. If a swarm intelligence tool fulfils the previous conditions, it can generate value for investment decisions. The MPT fails in a complex and correlated world. Risk is not assessed correctly. Crowds can help here because they aggregate vast amounts of information, beliefs and feelings. In this way, they can assess risk in situations when individual semi-rational agents fail.

4. Risk Assessment by Laymen

Hereafter it will be discussed whether the results achieved beforehand can be fruitful for the investment business of a bank. Therefore, these results will be combined and reviewed in consideration of that objective. Firstly, a distinction between experts and non-experts has to be made. After that, it will be shown why it is reasonable to criticise expertise and to take opinions of laymen into account in financial issues as well as on many other topics. The concept of how the investment business could benefit from predictions of laymen will be built on this discussion. Due to the lack of empirical evidence, this paper will propose a concept of how our thesis can be applied to a working tool and be the basis for further studies and experiments stressing this thesis. In our approach, we distinguish between experts and non-experts, or better yet, laymen. In this context, when referring to experts, we mean people working in the stocks and bonds department of a bank and are therefore confronted with stock markets daily (cf. Staël von Holstein 1972). They are experts in analysing data or making investment decisions based on these analyses. Anybody involved in an investment decision or the analysis leading to this decision is considered an expert. Corresponding to that, any person not involved in that decision-making process will be considered a non-expert and is therefore a potential participant of our tool. Though there are strong distinctions regarding the state of knowledge about stock markets among employees of a bank, this is useful to achieve a certain degree of diversity among the participating group (referring to the requirements for swarm intelligence in the prior section). Diversity is an inevitable prerequisite for achieving significant results.

Concerning forecasting events, different studies on probabilistic forecasting and information markets[1] have shown that non-experts are often as good as or sometimes even outperforming experts in their field. We will primarily rely on the results of Staël von Holstein (1972) on probabilistic forecasting related to the stock market, Yates, McDaniel, and Brown (1991) on probabilistic forecasts of stock prices and earnings and Chen, Chu, Mullen and Pennock (2005) on information markets versus opinion pools. Though there are distinctions between the approaches of the scientists named, they all lead to the conclusion that the accuracy of experts and laymen do not differ very much. The enquiry of the latter also admits to the conclusion that "averaging across all experts seems to result in better predictions than individual opinions and opinion pools with a few experts" (Chen et al. 2005: 9).[2] Since in-formation markets also outperform the single expert's judgement on average, it can be deduced that the consideration of aggregated opinions, regardless of whether they are experts' or laymen's, is a consistent way to improve the accuracy of predictions, even if isolated expert judgements are more accurate in some cases. The enquiry of Chen et al. has shown more extreme predictions (predicted probability of an event closer to 0 resp. 1)[3] tend to yield worse accuracy than the averaged and aggregated expert beliefs. It is noticeable that in the accuracy ranking compiled during the study, experts who were usually making more extreme

1 Information market: market, on which securities are traded that either P or non-P occurs. The payoff of each security is 100, the price for a security that p occurs, indicates the predicted probability of P.

2 Opinion pools: belief aggregation method, in this case, to aggregate experts' beliefs (cf. Yates p.1) Wo kommt das her? Seite 1? Jahreszahl angeben, etc.

3 More accurate predictions have to be more extreme judgements. Otherwise, they would be close to the average and would not occur as more accurate, but within the range of typical judgements.

predictions tended to rank lower (cf. ibid: 6). According to the findings of Yates et al., individuals with higher expertise even show a tendency to make more extreme judgements, resulting in worse accuracy (cf., 1991: 73). Hence, more extreme predictions are likely to have a worse average value than moderate predictions and are thus more risky. In conjunction with experts tending to predict in a rather extreme way, this allows for the assumption that experts' judgements strive towards risk.

Two findings of Staël von Holstein, namely that "people can quantify their beliefs reasonably well in probabilistic terms" (1972: 157) and the "relationship between accuracy and expertise [being] almost the inverse of what many people would expect" (cf. Yates et al. on Staël von Holstein 1991: 61), will be combined with the results of Yates and his colleagues hereafter. The results of the latter that will be considered now are support for the inverse relationship thesis, but also provide an explanation for that phenomenon. Experts' judgments are sometimes richer than those of laymen, but experts tend to be more likely to respond to irrelevant cues in a more extreme manner, since they are strongly convinced of the correctness of their beliefs, contrary to non-experts. Even if the cues were valid, due to the more extreme judgements resulting from the process, they are no guarantee for the enhancement of the judge's performance and rather increase risk. As there seems to be an inverse relationship between expertise and accurate predictions, and it seems possible to quantify non-experts' beliefs, which tend towards accuracy, it is reasonable that such laymen-based forecasts should be used more routinely in the financial world to gain information about stock markets. Although the studies seem to indicate that laymen are often just less inaccurate than experts and not necessarily accurate in absolute terms (cf. Yates et al. 1991: 75 ff.), a possible method to take these findings for real financial decisions into account should be considered. Even if these predictions lack the ability to legitimise decisions or replace an expert, making such probabilistic forecasts, when applied to investments, might be a helpful instrument to ease decisions and test if an expert's judgement is sound.

We now want to provide a concept for the development of a tool which applies the findings of the swarm intelligence section and the capabilities of non-experts' predictions and which can be employed in the investment department of a bank. This tool's purpose is to describe a possibility to improve investment decisions, using findings of behavioural finance, information markets and probabilistic forecasts. One result of the enquiries discussed be-forehand was that non-experts are capable of predicting changes in stock prices as well as experts. Now we want to refer to the definition of experts that we gave at the beginning of this section and exclude these individuals from participation in the mechanism, which this concept has as a result. This is due to the fact that if they were participating, they would change the outcome in an undesirable manner, as instances of displaying overconfidence and extreme beliefs would shift the aggregated average. As such a tool needs motivated and reliable participants, we argue that the pool of potential participants should be that particular bank's employees with the exclusion of the experts. Several advantages are associated with that. The reachability of many diverse individuals in a short amount of time eases the search for participants. But even more important is the ability to exchange and vary a huge number of participants at a time in order to avoid interference in the operational procedure of the bank. If the same employees were always asked to participate, they would be discouraged and distracted, influencing their working flow. As a result, the employees' performance as well as the accuracy of the tool would suffer.

It appears to be reasonable to base such a tool on the probabilistic forecast studies by Staël von Holstein and Yates and his fellows, since their results assume what this tool is supposed to supply. Certainly some adjustments have to be made. For the foregoing reasons, the tool cannot be as time-consuming as the surveys of the mentioned scholars and the procedure has to be simplified. Instead of asking those individuals participating for the predictions for a set of stocks and a grading of these predictions into five (Staël von Holstein), respectively six (Yates et al.), classes of percentage increase or decrease in price, the individuals should be consulted concerning only one singular stock at a time. Furthermore, they are supposed to state their belief only if a stock price increases or decreases in the long term[4], respectively to give advice to buy or sell (advice to buy corresponds to the belief in the increase in price, sell to the belief in the decrease), without predicting the range of variation. Indeed, the types of stocks have to be qualified. This tool will only apply to rather simple financials, such as shares, bonds, currencies, and gold. Additionally, to achieve the best and the most elaborate results from an employee, she should only be consulted once in a while, depending on the number of people contributing overall and the number of pieces of advice asked for by the investment department, but not more than once a month. For a significant outcome, a certain number of people have to contribute. To figure out what this critical mass is, further studies and experiments have to be conducted. But this mass should not exceed 200 people per valuation.

The prediction as to whether a stock price increases or decreases yields possibly observable issues. There is no data, however certain the participating individuals are about their predictions. In particular, it is not evaluated whether they were just guessing, or felt absolutely certain about

4 Short-term or day trades cannot be covered by such a tool, as they are often made within hours and the procedure of evaluation will take some time.

their decision. This might be remedied by asking for self-evaluated confidence. On account of this, a variation of the concept should be considered. In addition to predicting the direction of a price variation, the participants are asked how confident they are about this prediction. Since studies exist that detailed self-evaluation fails concerning confidence, this will be kept as simple as possible. The individuals are asked to measure their decision either as 'I am 5% sure', 'I am 50% sure' or 'I am 95% sure'. The former, basically, is equivalent to guessing or more pictorially, flipping a coin. The second means the individual is quite sure but not absolutely certain. The latter means that the particular individual is very sure about her decision; as we have seen in the former enquiry, such extreme confidence should be suspect to suspicion. Therefore, through a simple additional question, much data can be generated. To find out if this additional evaluation also holds additional value and which of the concepts responds better to the purpose of enhancing accuracy of stock price, predictions are also subject to further investigations, as is the relation between the additional data gained on confidence and the related predictions. It might be of great value to know whether higher values cohere with higher accuracy, or whether there is no relation or even an inverse one. The final result will be a mechanism of great value for an investment department of a bank.

5. Conclusion

First, it was argued that MPT does not yield its main task: to be risk reducing. The assumed rational decision makers tend to ignore risk - a fact that in turn leads to an indirect increase of risk. Behavioural finance tackles the assumption of an individual's ability to make rational decisions. Decisions are often made by instinct but are nevertheless appropriate and potentially generate a higher value. A further enquiry into that topic disclosed the great ability of a crowd to provide accurate answers and predictions. Since information markets and probabilistic forecasts adapt these findings and make them fruitful for different topics, the claim can be made that it is possible to use these outcomes to enhance risk assessment in the investment department of a financial institute. Experts' predictions regularly indicate less accuracy than aggregated predictions of laymen. It was shown that the findings can be utilised to enhance experts' judgements by developing an advisory mechanism based on probabilistic forecasts and behavioural finance. Therefore, it seems reasonable to conduct further research and implement such a mechanism for decision making in investments in order to reduce risk and enhance performance. Now, more than ever, the promising alternatives to traditional investment models should be taken advantage of.

References

Auckenthaler, C. (1994): Theorie und Praxis des modernen Portfolio-Managements, 2nd edition, Haupt: Bern.

Barberis, N. / Huang, M. (2001): Mental Accounting, Loss Aversion, and Individual Stock Returns, in: Journal of Finance, Vol. 56, No. 4, 1247-1292.

Barberis, N. / Thaler, R. (2003): A Survey of Behavioral Finance, in: Constantinides, G. M. / Harris, M. / Stulz, R. (eds.): Handbook of the Economics of Finance, Elsevier Science B.V.: Amsterdam, 1052-1090.

Chen, Y. / Chu, C.-H. / Mullen, T. / Pennock, D. M. (2005): Information Markets vs. Opinion Pools: An Empirical Comparison, EC '05, June 5-8. URL: www.consensuspoint.com/prediction-markets-blog/information-markets-vs-opinion-pools-an-empirical-comparison (accessed: 10.01.2015).

Fischer, L. (2010): Schwarmintelligenz, Eichenborn AG: Frankfurt am Main.

Mandelbrot, B. / Hudson, R. L. (2004): The (Mis)behavior of Markets. A Fractal View of Risk, Ruin and Reward, Basic Books: New York.

Markowitz, H. (1952): Portfolio Selection, Journal of Finance, Vol. 7 / No. 1, 77-91.

Markowitz, H. (2008): What to Do About the Financial Transparency Crisis, IFA Articles. URL: www.ifa.com/articles/Financial-Transparency-Crisis.aspx (accessed: 10.01.2015).

Page, S. E. (2007): The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools, and Societies, Princeton University Press: Princeton, NJ.

Razek, Y. H. A. (2011): An Overview of Behavioral Finance and Revisiting the Behavioral Life Cycle Hypothesis, in: The UIP Journal of Behavioral Finance, Vol. VIII / No. 3, 7-24.

Ricciardi, V. / Simon, H. K. (2000): What is Behavioral Finance?, in: Business, Education & Technology Journal, Vol. 2 / No. 2, 1-9.

Rottwilm, C. (2008): Being Harry Markowitz, in: Manager Magazin online. URL: www.manager-magazin.de/finanzen/geldanlage/0,2828,555749,00.html (accessed: 10.01.2015).

Simon, H. A. (1956): Rational choice and the structure of the environment, in: Psychological

Review, Vol. 63 / No. 2, 129-138.

Skjong, R. / Wentworth, B. H. (2001): Expert Judgement and Risk Perception, Proceedings of the eleventh (2001) International Offshore and Polar Engineering Conference, Stavanger, Norway, June 17-22, URL: http://research.dnv.com/skj/papers/skjwen.pdf (accessed: 10.01.2015).

Stäel von Holstein, C.-A. S. (1972): Probabilistic Forecasting: An Experiment Related to the Stock Market'. New York: Academic Press, Inc., Organizational Behavior and Human Performance, No. 8, 139-158.

Wagemann, F. (2009): Die Markowitz Theorie bei vermögenden Privatkunden: Spielt Behavioural Finance eine Rolle?, GRIN: München.

Yates, F. / McDaniel, L. / Brown, E. (1991): Probabilistic Forecasts of Stock Prices and Earnings: The Hazards of Nascent Expertise. New York: Academic Press, Inc., Organizational Behavior and Human Decision Processes, Vol. 49, Issue 1, 60-79.