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An Experimental Study

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# Lower Partial Moments As Measures of Perceived Risk - An Experimental Study

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**Abstract:**
The paper reports the results of an experiment on individual investors' risk perception in a stock market context under two different modes of information presentation (framings). While the concentration on two moments of a return distribution has been a cornerstone of neo-classic finance theory from the start (Markowitz 1952) an alternative's mean and variance have been selected more by convenience and ease of computation than by theoretical or empirical justification. Even though the most influential models are based on variance as risk measure there has always been much discontent with this proposal. The symmetrical nature of variance does not capture the common notion of risk as something undesired, e. g. negative deviations from a reference point. Instead, lower partial moments (LPM) seem to be more appropriate for measuring risk.
The purpose of this paper is to examine experimentally private investors' risk perception in a financial context. The focus is on the correspondence of people's risk perceptions with specific LPMs. The main findings can be summarized as follows. First, symmetrical risk measures like variance can be clearly dismissed in favor of shortfall measures like LPMs. Second, the reference point (target) of individuals for defining losses is not a distribution's mean but the initial price in a time series of stock prices. Third, the LPM which explains risk perception best is the $LPM_0$, i. e. the probability of loss. Fourth, the framing of price distributions (histograms versus charts) exerts a significance influence on average risk ratings, the latter being higher for the histogram framing. Fifth, positive deviations from an individual reference point tend to decrease perceived risk.



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# 1 Introduction

Risk and its measurement are still fascinating topics for studies in decision making in general and in finance in particular. The overwhelming number of papers devoted to risk taking and risk perception – starting with Allais' and Ellsberg's demonstrations that expected utility theory (EUT) is not able to describe people's risk preferences – concludes that a normatively plausible theory does not necessarily mean that people accept its implications or follow its axioms. While the development of generalisations of EUT during the last 15 years (cf. Weber/Camerer 1987 for an overview) has been and still is a field of research that attracts much attention and effort, one shortcoming of these approaches lies in the implicit rather than explicit consideration of risk as an alternative's attribute. The reduction of situational complexity is one aim a practically useful decision model should accomplish. One means to accomplish this aim is the representation of a probability distribution by those of its moments that characterize it entirely.
The connection between EUT and the intuitively appealing way using moments lies in the fact that an alternative's utility can be decomposed into two components, one attribute representing the subjective value and one representing the risk associated with it. The development of these risk-value models (an excellent overview provide Sarin/Weber 1993; Jia/Dyer 1997) has flourished during the last couple of years, while the original idea of explicitely conceptualizing risk as a decision variable dates back to Allais (1953) and Coombs (1969).

This development in decision theory has been accompanied by an independent movement in the finance theory literature where lower partial moments (LPMs) have found renewed interest after their introduction by Bawa (1975). While the concentration on two moments of a return distribution has been a cornerstone of neoclassic finance theory since its beginnings (Markowitz 1952) an alternative's mean and variance have been selected more by convenience and ease of computation than by theoretical or empirical justification. The theoretical argument against the mean-variance-model centers around the unreasonable properties of a quadratic utility function which exhibits increasing absolute and relative risk aversion. The specific form of the utility function is irrelevant if returns follow a normal probability distribution. However, international evidence demonstrates that security returns rather follow a leptokurtic distribution.
Although the most influential models of capital asset pricing are based on variance as risk measure there has always been much discontent with this proposal. The symmetrical nature of variance which assigns the same weight to positive as to negative deviations from the expected value does not capture the common notion of risk as a negative, undesired characteristic of an alternative. Therefore, LPMs intuitively seem to be more appropriate for measuring risk.

The purpose of this paper is to experimentally examine private investors' risk perception in a financial decision context. The next paragraph deals with approaches suggesting optimal ways for decisions under conditions of risk. The relationship between the most prominent normative theories for decisions under risk are discussed. Afterwards the correspondence of several measures of risk with these theories will be analysed. LPMs are shown to be appropriate measures of risk under reasonable assumptions on a decision maker's risk preference. Furthermore, LPMs are contrasted with other measures of risk both from economics and from psychology. The advantage of LPMs over variance, the traditionally most frequently used risk measure in financial economics, is shortly discussed on the basis of theoretical arguments. Section 3.1 describes the experimental design and developes several hypotheses. In section 3.2 the results are presented and discussed. The final section 4 draws several conclusions and points to some directions for future research.

The main results are, first, that symmetrical risk measures like variance can be clearly dismissed in favor of shortfall measures like LPMs. Second, the reference point (target) of individuals for defining losses is not a distribution's mean but rather the initial price in a time series of stock prices. Third, the LPM which explains risk perception best is the $LPM_0$, i. e. the probability of loss. Fourth, the framing of price distributions (histograms versus charts) exerts a significant influence on average risk ratings, the latter being higher for the histogram framing. Fifth, positive deviations from the individual reference point tend to decrease perceived risk. It is found that the shape of a distribution is also of relevance and that the impact of skewness on investors' risk perception is not unanimous.

# 2 Expected Utility Theory, Stochastic Dominance, and Lower Partial Moments

## 2.1 Normative Theories for Decisions under Risk

The most widely accepted normative theory for decisions under risk is the von Neumann-Morgenstern theory. Although the normative appeal of EUT is commonly acknowledged (Edwards 1992), its lacking power to explain people's preferences, the difficulty and vagueness in the process of eliciting utility functions and the consideration of limitations of human information processing capacities lead to alternative theoretical accounts.

The first alternative considered here are the rules of Stochastic Dominance (SD), a concept developed very early this century (cf. the references cited by Kroll/Levy 1980) but not introduced into economic theory before the late 60s (Hadar/Russell 1969; Hanoch/Levy 1969; Rothschild/Stiglitz 1970; Whitmore 1970). The central idea behind the SD approach is that it tries to simplify the decision problem by sorting out dominated alternatives. The set of alternatives that have to be examined in more detail is diminished in this first step. Individuals are still believed to maximize their subjective utility but they only have to specify their utility function in a very rough manner, i. e. the knowledge of a concrete function is replaced by assumptions about classes of functions or properties of the functions.

SD allows pairwise comparisons of cumulative distributions functions F and G. In the following, F dominates G by First (FSD), Second (SSD), or Third Order Stochastic Dominance (TSD), if and only if (Hadar/Russell 1969; Hanoch/Levy 1969; Whitmore 1970; Bawa 1975; Fishburn/Vickson 1978; Levy 1992):

$$F(x) \leq G(x) \; \forall \, x \in \Re \qquad \text{(FSD)}$$

$$\int_{-\infty}^{t} [G(x) - F(x)] dx \geq 0 \; \forall \, t \in \Re \qquad \text{(SSD)}$$

$$\int_{-\infty}^{t}\int_{-\infty}^{v}[G(x)-F(x)]\,dxdv \geq 0\ \forall\ t, v \in \Re \text{ and } E[F(x)] \geq E[G(x)] \qquad \text{(TSD)}$$

(at least one strict inequality for t must hold in each of the three definitions).

It can be shown that the preference order resulting from the application of FSD, SSD, and TSD is identical to the order generated by maximization of utility for the specific classes of utility functions:

$$U_1 \equiv \{u(x) | u'(x) > 0\ \forall x \in \Re\} \qquad \Leftrightarrow \text{FSD}$$

$$U_2 \equiv \{u(x) | u'(x) > 0 \text{ and } u''(x) < 0\ \forall x \in \Re\} \qquad \Leftrightarrow \text{SSD}$$

$$U_3 \equiv \{u(x) | u'(x) > 0; u''(x) < 0 \text{ and } u'''(x) > 0\ \forall x \in \Re\} \quad \Leftrightarrow \text{TSD}$$

The class of utility functions $U_1$ includes decision makers with a positive marginal utility for money which is an undisputed assumption since it holds for all kinds of risk propensity and it only implies that one prefers more money to less. $U_2$ reduces the set of admissible utility functions to all risk averters and $U_3$ further requires the individual to prefer positively skewed distributions (more probability in the right tail). It has been shown empirically that investors display this kind of skewness preference (Arditti 1967; Conrath 1973; Friend/Westerfield, 1980; Cooley 1977; Levy/Sarnat 1972, p. 247; Scott/Horvath 1980. However, different results are presented in Francis 1975 and Tan 1991). Note that $U_3$ contains both investors with decreasing and increasing absolute risk aversion.

The applications of the principles of SD are widespread including portfolio management, optimum production, option valuation and the analysis and definition of risk. In addition, SD has been proved to be compatible with nonlinear utility theories (Fishburn 1989), has been extended to the multipe-riod case, and to ambiguous distributions (Langewisch/Choobineh 1996). Perhaps the most serious problem in applying SD rules to real settings lies in their computational complexity for a wide range of problems. Since the theory still requires the decision maker to take the complete distribution of outcomes into consideration, only a slight reduction of complexity is achieved. But the simplification of decision rules is urgently needed regarding the limited information processing capacities of human beings (see Russell/Seo 1989 and Kroll/Levy 1980 for attempts in simplifying SD rules). It would be much easier to compare investment alternatives if one could concentrate on a few number of attrib-utes which comprise the complete information about the distribution under consideration. This idea lies at the heart of risk value models that separate expected utility in only two parameters, value (i.e. a high return) and risk (i. e. the avoidance of risk).

## 2.2 Risk-Value Models and Measures of Risk

Since the notion of risk cannot be separated from the axioms underlying the definition of rational risky behavior there is no objective definition of risk which could be accepted unanimously. The se-arch for definitions of risk which apply to a large group of individuals lead to the concept of increa-sing risk, first proposed by Rothschild and Stiglitz 1970 (for a recent generalization cf. Machi-na/Pratt 1997). This broad conception of risk could be made more operational if it is possible to find appropriate risk measures. Obviously, possible risk measures are the moments characterizing a pro-

bability distribution. Using all the moments of a distribution in making a decision yields the same result as maximizing its expected utility. As a consequence, expected utility is a function of all moments of a distribution. This means that an ordering of alternatives according to SD rules implies also an ordering according to the moments of a distribution. The decision task can be simplified substantially if it is possible to focus on a few moments and thereby still maximizing expected utility. This form of complexity reduction is the fundamental starting point of risk value-models.
While the value parameter is unambiguously defined as expected value the risk parameter in these models as well as the combination rule for integrating value and risk depend on the assumptions of the model. Since this experimental study only analyses risk perception and does not require subjects to choose between alternatives, the following will focus on risk measures leaving aside specific models combining risk and value into a preference index (cf. Dyer/Jia 1997; Sarin/Weber 1993 for summaries of relevant models).

One class of measures of risk which are consistent with the definition of increasing risk (cf. Rothschild/Stiglitz 1980) for arbitrary probability distributions are the so-called Lower Partial Moments (LPMs). These were independently introduced in (financial) economics by Bawa (1975) and Jean (1975). LPMs are measures of downside or shortfall risk in the sense that only negative deviations from a target outcome are taken into consideration (cf. Fishburn 1977; Stone 1973; Dyer/Jia 1996; Menezes/Geiss/Tressler 1980 for similar risk measures). In the case of continuous distributions with outcomes $x \in [-\infty; t]$ each LPM can be computed as follows:

$$LPM_n^t(x) = \int_{-\infty}^{t} (t - x)^n \, dF(x) \,,$$

where t is the target from which deviations are measured, x are the outcomes of the probability distribution and f(x) is its density function. The exponential variable n determines the weight the investor places on deviations. Positive deviations from t are considered to be desirable and consequently do not have an impact on an alternative’s risk. Some of the most frequently used risk measures are special cases of LPMs, for example the semi-variance corresponds to the LPM with the distribution’s expected value as target outcome and a weighting coefficient of n = 2 (subsequently denoted as $LPM_2(\mu)$), the probability of loss equals the $LPM_0(t)$ and the expected loss is the $LPM_1(t)$. Note that the target t can be thought of as a reference point separating gains and losses and therefore remains open to further specification in dependence on the person and the situation under consideration.

LPMs are applicable to arbitrary distributions and consistent to utility functions with plausible properties (see below). The LPM approach is of special importance for applications to portfolio theory. In the case of asymmetrical return distributions (e. g. options or hedge portfolios) the appropriate risk measure should be asymmetrical in nature, too (Schröder 1996).

A preference ordering according to the LPMs of two distributions corresponds to the ordering derived from SD rules (and from maximizing expected utility) for the following classes of utility functions:
For F to be preferred to G it is necessary and sufficient that (Bawa 1980, p. 64)

- for all $u(x) \in U_1$: $LPM_{0,F}(t) \leq LPM_{0,G}(t)$ $\forall$ t; with at least one strict inequality for t.
- for all $u(x) \in U_2$: $LPM_{1,F}(t) \leq LPM_{1,G}(t)$ $\forall$ t; with at least one strict inequality for t.
- for all $u(x) \in U_3$: $LPM_{2,F}(t) \leq LPM_{2,G}(t)$ $\forall$ t; with at least one strict inequality for t and $E(x_F) \geq E(x_G)$.

For financial economics it is particularly interesting that variance is only compatible with definitions of increasing risk in the case of distributions that can be completely described by two moments (e. g. normal or lognormal distributions) or in the case of quadratic utility functions. This means that some risk averse investors maximize their expected utility by choosing alternatives with higher variance when means are equal and the distributions under consideration are not of the 2-parameter family.

## 2.3 Lower Partial Moments in Finance Theory

The arguments underlying the discussion about reasonable risk measures have strongly influenced financial economics as well. While the number of alternative asset pricing theories based on other risk measures than variance and more realistic assumptions about human behavior is still very small (for notable exceptions cf. Weber 1990; Franke/Weber 1997) there have been quite numerous efforts to establish portfolio selections algorithms and capital asset pricing models on the basis of shortfall risk measures.

Bawa (1975) was the first to show that for arbitrary probability distributions mean-LPM rules are in accordance with the principles of SD and that the well known mean-variance criterion is only a special case of this concept. What distinguishes his approach from others is that it stands on the firm theoretical basis of SD and that it defines conditions under which a specific mean-LPM rule is in accordance with the conceptions of FSD, SSD, TSD etc. Besides its theoretical soundness the LPM approach has the advantage that most other risk measures are only special cases of LPMs. Therefore, Bawa’s proposal is the most general and should be widely acceptable.

An asset pricing model using a mean-LPM decision rule was developed soon after (Bawa/Lindenberg 1977). The structure of this model is basically the same as in the CAPM. The only difference is the substitution of beta by a LPM-beta. For normal and Student-t-distributions of returns the LPM based model reduces to the conventional CAPM. Empirical and simulation studies show the superiority of mean-LPM based portfolio selection criteria towards the traditional mean-variance based approach under the assumption of shortfall-risk oriented investors (Porter/Gaumnitz 1972; Russell/Seo 1980; Leibowitz/Langetieg 1989; Nawrocki/Staples 1989; Sortino/van der Meer 1991; Sortino/Forsey 1996; Harlow 1991). An empirical study using data from the German stock market shows that regressions with LPM-betas explain stock returns better than regressions with traditional betas. Unfortunately, the explanatory power is very low for both (Reichling 1997). Harlow/Rao (1989) conclude from estimations using stock market data that a $LPM_2$ with a target return representing the average market return is reflected in market prices. But they only use this second order LPM and do not test for alternative weighting coefficients.

In spite of the development of models for capital asset pricing based on LPMs the empirical question of whether investors risk perception is really reflected by LPMs and which target outcome and weighting coefficients are valid for the majority of investors is still unanswered. The experiment outlined in the next section takes up this question and tries to shed some light on these issues.

# 3 The Relation between Perceived Risk and Lower Partial Moments

## 3.1 Design and Hypotheses

The main interest of this study concerns the question if people perceive risk in a similar manner as LPMs measure risk. In order to examine the risk perception of individual investors more closely and to see which of the different risk measures deducted on theoretical grounds pass the empirical test a study was designed to identify the characteristics of a distribution that influence risk perception. It should be stressed that this examination concentrates entirely on risk perception and does not address people's risk preferences or risky choice. The important distinction between risk perception and risk attitude which both moderate risk behavior has not been drawn in the relevant literature until a few years ago (Sitkin/Pablo 1992; Sitkin/Weingart 1995; Weber/Milliman 1997).

**Design overview**

The experimental study first focusses on the usefulness of symmetrical risk measures (e. g. variance or mean absolute deviation) compared to asymmetrical measures like semi-variance or probability of loss that are only special cases of LPMs. In a second step, it is investigated which specific LPMs are most closely corresponding to subjects risk perception. Ultimately, this is an empirical question since it cannot be theoretically determined which LPM represents peoples risk perception best. This implies that the target outcome and the weights of the deviations from this target have to be specified. Of course, for each individual there is a specific target and weight depending on his risk propensity, i. e. the more risk averse a person the higher the target and the heavier the weight that is attached to deviations from this target in calculating the subjective risk index. In order to gauge weighting coefficients for each subject a high number of risk comparisons would be necessary. To circumvent this problem the study focuses on average instead of individual risk perception. Therefore, mainly between-subjects comparisons are drawn even though some analyses are possible on a within-subject basis, too.

**Stimuli**

Eight hypothetical discrete stock price distributions were chosen as stimuli. In order to examine the effect of different target outcomes and shapes of distributions the alternatives were constructed in a way that their variance is almost identical while there are two different means and four different shapes of distributions, namely a normal distribution, a uniform distribution, and two distributions with a positive and a negative skewness. Figure 1 gives an overview of the main characteristics of the eight stocks.

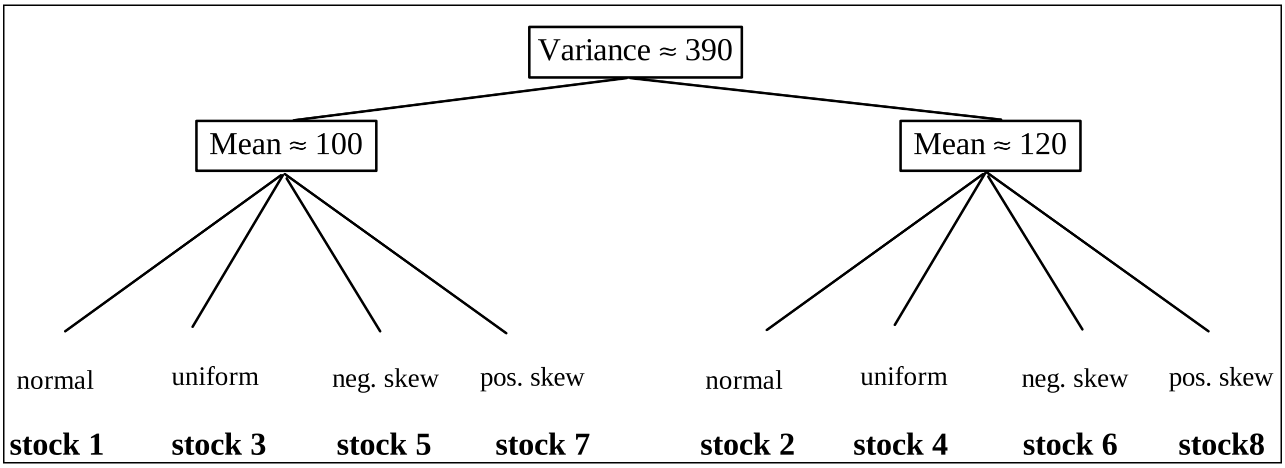


**Figure 1: Stimuli used for risk rankings.**

Each stock distribution consisted of 52 hypothetical end-of-week prices for the next year with an initial price of 100 for each stock. This should make risk comparison between the stocks as easy as possible. Subjects were instructed to consider the prices as forecasts drawn from an expert panel. Even in the absence of forecast errors the investment decisions are not risk-free since it was pointed out in the instructions that a stock is strictly bought at the beginning of the period under consideration while the selling date is random (e. g. due to unexpected liquidity shortages). The distributions were either displayed (framed) as charts or as histograms with equidistant intervals. It is important to note that the latter visualisation mode does not allow the subjects to infer any information about the sequence of prices. It is just known that the first price is 100 for all stocks. Further, the minimum and the maximum price within the next year was displayed separately. To eliminate potential effects of a trend in the stock prices the pattern for all eight stocks was roughly the same: an early decline in prices followed by an increase in the middle of the year and a decrease in price during the last periods (see appendix 1a for the stimuli used and the risk measures associated with each stock).

Subjects had to rate two groups of four stocks each on a scale from 0 (no risk) to 100 (very risky) according to their subjective risk perception. They were explicitely instructed not to think about preferences for stocks but only to rate them on the basis of their inherent risk. Each subject had to rate all eight stocks, four of them displayed as charts and the other four displayed as histograms. But, in order to conceal the main purpose of the experiment, the stocks in these two groups had a different level of mean. Therefore, a subject expressed ratings for all eight stocks but in two different conditions. One group rated stocks 1, 3, 5, and 7 (mean ≈ 100 each) displayed as histograms and, on a separate paper, stocks 2, 4, 6, and 8 (mean ≈ 120 each) in the chart framing. For the other group of participants the order was reversed. The stocks within a group of four always had equal means. To make comparisons easier the four stocks are displayed together on one sheet of the questionnaire. The order of stocks in the questionnaire and the sequence of the two different displays were randomized and did not influence the ratings. The displays used are shown in appendix 1b together with the most important statistical parameters in appendix 1c.

### Subjects

The study was conducted as a classroom experiment at the University of Bamberg in December 1997 and did only require 10-15 minutes. The 98 graduate and 101 undergraduate students of business administration were not paid for their participation in the experiment. Since the answers from the two groups do not differ the answers are pooled and the results are presented for the total group of 199 subjects (if not indicated otherwise). Although it is sometimes criticized to use students as subjects in experiments (Friedman/Sunder 1994; Cunningham/Anderson/Murphy 1974) they seem to be suitable for this study because its main interest is an intuitive understanding of risk of individual investors. Professionals like bank employees or stock traders/brokers as participants would not have served the purpose of the study since the professional specialisation in this field (risky financial decisions) most probably distorts the intuitive feeling of risk.

### Hypotheses

Theoretically, it is only possible to separate classes of utility functions with plausible characteristics and propose risk measures that are compatible with these functions. Each subject should be characterized by specific parameters that reflect his subjective risk attitude. If one assumes a positive marginal value of money, risk averse behavior, and a preference for positive skewness either alternatively or in combination, alternatives with the same mean can be unambiguously ordered according to their $LPM_0$, $LPM_1$, and $LPM_2$.

Following the argumentation outlined above and taking empirical results from a substantial number of studies into account it is plausible to hypothesize that asymmetrical risk measures fit subjective risk ratings better than symmetrical risk measures. If one compares LPMs with the mean as target outcome and a weighting coefficient of $n = 2$ ($LPM_2(\mu)$ which is the semivariance) to variance as a traditional two-sided measure one should get the following result:

***Hypothesis 1*: *The correspondence between LPMs and subjects' risk ratings is stronger than that between variance and subjects' risk ratings.***

An ordering of the eight stocks according to their risk measured by $LPM_2(\mu)$ gives ($S_X < S_Y$ denotes that stock X has a lower risk than stock Y): $S7 \approx S8 < S1 \approx S3 < S2 \approx S4 < S5 \approx S6$.
If variance described people's risk ratings best no difference in risk could be detected between the eight alternatives. Another way to operationalize hypothesis 1 is the comparison of correlation coefficients between risk measures and individual risk ratings. If the above hypothesis is to be supported the average coefficients should be higher for $LPM_2(\mu)$ compared to variance.

The motivation behind the next hypothesis is the consideration that people frequently use the status quo as a reference point (target outcome) for risk judgements. There is ample evidence for the importance of the status quo, i. e. the starting price of 100 in this study (Samuelson/Zeckhauser 1988; Kahneman/Knetsch/Thaler 1991). In addition, qualitative answers of subjects suggest the special role of the first stock price for risk judgements. This reasoning leads to

***Hypothesis 2***: *LPMs with the starting price of 100 as target outcome correspond to a higher degree to subjects' risk ratings than LPMs with the mean as target.*

If one uses the $LPM_2(100)$ a different ordering results: S8 < S4 ≈ S2 < S6 << S7 < S1 ≈ S3 < S5. Again, one can test if average ratings for the stocks differ in the proposed direction. Alternatively, if hypothesis 2 is correct the correlation coefficients should be larger for $LPM_2(100)$ in comparison to $LPM_2(\mu)$. Furthermore, the eight alternatives were designed beforehand in a way that allows to distinguish them easily. Therefore, subjects should be able to detect differences in risk between the alternatives. Due to the construction of the distributions the risk ordering is also a preference ordering according to SD rules (see appendix 2). Since estimation risk does not affect the basic properties of SD, empirical distributions can be used to apply SD criteria (Bawa 1980). This means that this study does not inherit additional problems by constructing distributions rather than taking realizations from a theoretical probability distribution. While four pairs of stocks can be ordered by means of FSD (these are the pairs 1-2, 3-4, 5-6, and 7-8) comparisons between other pairs are not clear-cut. However, the indicated order should hold irrespective of the specific target intuitively applied by the participants.

The preference for positively skewed distributions seems to be a reasonable, although not indisputable (Lopes 1984; Tan 1991), assumption. Furthermore, the magnitude of losses in the sense of negative deviations from the target outcome should also be relevant for risk averse investors. The first assumption about individual behavior entails both TSD and the application of the $LPM_2$, the second assumption justifies the $LPM_1$ (simultaneously implying SSD). Therefore one can assume that:

***Hypothesis 3***: *Individuals' average risk ratings are more compatible with LPMs of higher order, i. e. larger deviations from the target outcome are assigned larger weights.*

Since the application of $LPM_0$, $LPM_1$, and $LPM_2$, respectively, corresponds to FSD, SSD, or TSD the ability of these shortfall measures to explain subjects' risk perception provides also indirect evidence of their risk preference.

A number of studies in human decision making show that the framing of alternatives (i. e. the mental representation of the alternatives in a particular situation; Tversky/Kahneman 1981) influences peoples decisions (Kühberger 1997). The specific frame a subject adopts is influenced by the formulation and presentation of the decision task. The two presentation modes used in this study to display the distribution of stock prices are assumed to have an impact on average risk perception. The consideration of empirical results on this phenomenon leads to:

***Hypothesis 4***: *The presentation mode of the stocks influences individual risk ratings.*

A more specific formulation of the hypothesis with regard to the consequences that result from a different framing is not possible, because until today, no theory exists that allows us to predict framing effects (Fischhoff 1983; Frisch 1993). Furthermore, this hypothesis is predominantly tested on a between-subject basis in conjunction with the other three hypotheses. However, a direct test in a within-subjects design is conducted separately.

## 3.2 Results and Discussion

If variance is an appropriate measure of perceived risk the average risk ratings for the eight stocks must not differ significantly since all stocks had approximately the same variance. As a test for differences in means (Duncan test) shows that the ratings for the stocks are different on a very high significance level ($\alpha < 0.0001$). Consequently, hypothesis 1, i.e. variance as a special case of a symmetrical risk measure do not capture people's risk perception, is confirmed by this result. The results are qualitatively the same for other symmetrical measures like the absolute deviation from the mean. Variance has to be dismissed as a risk measure. Instead, the class of LPMs is to be preferred as measures of risk perception. Table 1 displays the ranking of the stocks with the corresponding mean ratings results (a higher rating represents larger subjective risk) for all 199 subjects. The stocks are ordered according to their risk implied by semivariance giving the order S7 ≈ S8 < S1 ≈ S3 < S2 ≈ S4 < S5 ≈ S6 (see above).

**Table 1: Mean ratings of perceived risk for the eight stocks in dependence on framing**

| **stock** | **S7** | **S8** | **S1** | **S3** | **S2** | **S4** | **S5** | **S6** |
|---|---|---|---|---|---|---|---|---|
| **mean rating** | | | | | | | | |
| both framings | 63.1 | 50.6 | 46.9 | 46.0 | 39.6 | 42.9 | 43.1 | 41.3 |
| (standard deviation) | (20.9) | (23.5) | (17.1) | (21.8) | (18.6) | (21.6) | (21.8) | (22.6) |
| histogram | 67.2 | 48.6 | 49.0 | 50.5 | 40.1 | 47.3 | 35.4 | 41.4 |
| (standard deviation) | (20.5) | (21.8) | (17.4) | (24.7) | (16.4) | (23.6) | (21.6) | (22.9) |
| chart | 59.1 | 52.7 | 44.8 | 41.4 | 39.0 | 38.4 | 50.7 | 41.2 |
| (standard deviation) | (20.6) | (24.9) | (16.6) | (17.6) | (20.6) | (18.3) | (19.3) | (22.2) |

The analysis of differences in means for both framings taken together shows that stock 7 is unanimously judged as the by far riskiest stock. The two stocks with the lowest risk (S2, S6) are significantly different from stocks 1 and 3. The latter being like a demarcation line that segregates stocks 2, 4, 5, 6 from 1, 3, 7, 8. The risk comparisons between pairs of stocks are analyzed more deeply in connection with hypothesis 3 (see below).

The dependence of these results on the framing of stocks' distributions is shown in the last two rows of Table 1. The inspection of the results for the histogram presentation reveals that (compared to the average of all subjects) the perceived risk increased markedly for stocks 1, 3, 4 and 7. On the other hand, stock 5 is judged by far less risky, and stocks 2, 6, and 8 are assigned almost the same risk rating. Within this presentation mode the perceived risk of stock 7 is still a lot higher than the risk of all other stocks. If the distributions are displayed as charts the perceived risk is still more or less the same for stocks 2 and 6, it increases clearly for stocks 5 and slightly for stock 8, and decreases for stocks 1, 3, 4, and 7 compared to the average of all subjects. Stock 7 is significantly different from the rest, again.

A comparison of the risk ratings for the eight stocks between the two framings (t-Test for differences in means) shows that the perceived risk for stocks 2, 6, and 8 is independent from framing. The presentation of distributions as histograms leads to significantly ($\alpha < 0.1$) higher risk ratings compared to the charts framing for the other stocks with the exception of stock 5, to which a higher risk is assigned if it is displayed as a chart.

The average correlation coefficient between risk ratings and the standard deviation compared to that between risk ratings and the $LPM_2(\mu)$ (semi-variance) is higher (cf. Table 3). The difference is not significant, though. Even more irritating is the fact that both coefficients show a negative sign indicating that a higher standard deviation and a higher semi-variance tend to decrease perceived risk. This may be caused by the risk reducing property of positive deviations from the reference point (see discussion below). The other LPMs with the mean as target, besides $LPM_0(\mu)$, are not superior to the standard deviation. This leads to the question which target outcome should be used to define an appropriate LPM which is able to capture intuitive notions of risk.

The second hypothesis takes up this question and focuses on the reference or target outcome that is used by the majority of subjects to calculate an alternative’s LPM. As outlined above, some empirical arguments point to the starting price of 100 as target instead of the distribution’s mean. If this was the case one would expect that stocks with even numbers show a lower average risk rating than stocks with odd numbers. If subjects use the mean as target instead then there should be no difference in risk between stock pairs 1–2, 3–4, 5–6, and 7–8.

Perhaps, one side note is appropriate here. It is not claimed that people really calculate their subjective measure for perceived risk in the same way a LPM is formally constructed. But if LPMs capture the intuitive notion of risk for most people there has to be a strong correspondence between their answers (risk ratings) and analytically determined LPM.

The results in Table 1, p. 10 reveal that there is a significant difference in perceived risk between these pairs, at least for pairs 1–2 and 7–8 (each $\alpha < 0.001$; Mann-Whitney-U-Test) while for the pair 3–4 the difference is insignificant but in the direction expected. The framing of distributions does not influence these relations. This changes with regard to stocks 5 and 6. While stock 5 is significantly less risky ($\alpha < 0.1$) in the histogram display it is judged riskier than stock 6 in the chart display ($\alpha < 0.001$). Looking at the distributions (cf. appendix 1b), it seems likely that the shape of the distribution exerts a stronger influence than the difference in means. It can be established that the pairwise comparisons tentatively support hypothesis 2, i. e. the starting price of 100 (the status quo) seems to be more important as target than the mean of a distribution. For the majority of pairwise comparisons this risk ordering also accords to FSD relations (cf. the cumulative distributions in appendix 2) since S1 > S2, S3 > S4 etc. (> meaning „is riskier than“) creates a preference relation between the alternatives. The ability of individuals to detect stochastic dominance relations between pairs of the eight stocks seems to be relatively good if one takes mean ratings for this assessment (see above).

To sum up, it can be tentatively established that subjects are able to detect the (risk) dominance of stocks with even numbers over stocks with odd numbers. A further field of interest is the comparison of stocks within each group of four, because the stocks in each group (i. e. for each level of mean) differ in their shape and consequently in their higher moments. Table 2 shows pairwise comparisons within the two groups of stocks and reveals significant differences between ratings (Mann-Whitney-U test). These differences are interpreted below taking SD relations into consideration.

**Table 2: Pairwise comparisons of average risk ratings for the stocks**

| | both framings | | | histogram framing | | | chart framing | | |
|---|---|---|---|---|---|---|---|---|---|
| **stocks** | **S3** | **S5** | **S7** | **S3** | **S5** | **S7** | **S3** | **S5** | **S7** |
| **S1** | > | > ** | < **** | < | > **** | < **** | > | < ** | < **** |
| **S3** | – | > | < **** | – | > **** | < **** | – | < **** | < **** |
| **S5** | – | – | < **** | – | – | < **** | – | – | < **** |
| | **S4** | **S6** | **S8** | **S4** | **S6** | **S8** | **S4** | **S6** | **S8** |
| **S2** | < | < | < **** | < ** | = | < *** | = | < | < **** |
| **S4** | – | > | < *** | – | > * | < | – | < | < **** |
| **S6** | – | – | < **** | – | – | < ** | – | – | < *** |

> (<) indicates that the stock in the row is more (less) risky than the stock in the column.
* (**; ***; ****) indicates that the difference in risk is significant to the level of 0,1 (0.05; 0.01; 0.001).

The analysis of SD relations between the eight stocks yields the following results: If one looks at the stocks with odd numbers from a theoretical perspective one can conclude that stock 1 dominates (is less risky than) stock 3 according to SSD and stock 5 according to TSD, but the dominance over stock 7 is not strictly unequivocal for both SSD and TSD. Stock 3 dominates stock 5 only in the sense of TSD while the SSD dominance does not hold throughout, stock 7 is strictly dominated by stock 3 in the sense of SSD and TSD, instead. Comparing stock 7 to stock 5, there is no clear SSD or TSD relation but the latter tends to dominate the former.

This pattern is also revealed by the combined risk ratings for both framings. The histogram framing leads to an even more pronounced mirror image of the theoretical order. Besides the insignificant and reversed relation between stocks 1 and 3 all other relations are now highly significant and in the direction derived from theoretical considerations. For the chart frame the picture changes with respect to stock 5. Although the dominance relation between stock 5 and stocks 1 and 3 are not very clear-cut, the overall order is significantly reversed which suggests that the histogram framing allows subjects better to intuitively follow principles of SD.

The theoretical SD relations for the group with even numbers imply that stock 2 tends to dominate stock 4 although SSD and TSD do not hold strictly. No preference order can be established along SSD and TSD between stocks 2 and 6 while stock 8 is clearly dominant for both SD rules. The dominance relation between stocks 4 and 6 is ambivalent again, while stock 8 tends to dominate stock 4 both in the sense of SSD and TSD. A difference in preference between stocks 6 and 8 cannot be established using SD rules, too.

This weak theoretical pattern is neither followed by the histogram group nor by the chart group. While stock 8 is not supposed to be a very risky stock within this group it is actually judged riskier than the other three stocks. The differences in risk are most significant in the chart frame. Like the theoretical analysis suggests the dominance/risk relations between stocks 2, 4, and 6 are not unidirectional and with few exceptions not significant. The difference between the two groups may stem from the fact that the mean equals the starting price for stocks with odd numbers while in the other group the two values differ. Maybe this causes the indeterminancy of results for the even number group. Since the analysis does not render unambiguous results it is not possible to favour a specific LPM of higher order than 1.

Since the shape of the eight distributions is easily conceivable only on the basis of histograms the shape should influence ratings more strongly in this framing than in the chart framing. This is the case for the stocks with the lower mean where most risk relations are in the expected direction and significantly so. For the high mean group the effect of framing only partially supports the generation of ratings in accordance with theoretical measures. This is especially true with regard to the risk rating for stock 8 which is judged riskier than theoretically predicted under the assumption of decreasing absolute risk aversion.

Another method to examine whether different LPMs are appropriate to explain individual risk ratings is to analyse correlations between subjective ratings and risk measures. The rank correlation coefficients are displayed in Table 3 for the total sample and the two framing groups (of approximately equal size).

**Table 3: Pearson correlation coefficients between risk measures and risk ratings**

| **Risk measure** | **Pearson correlation coefficients** | | | |
|---|---|---|---|---|
| | both framings | histogram | chart | sign. |
| $LPM_0(100)$ | .263 | .3323 | .1931 | .035 |
| $LPM_1(100)$ | .165 | .1649 | .1649 | n.s. |
| $LPM_2(100)$ | .114 | .0782 | .1494 | n.s. |
| $LPM_0(\mu)$ | .190 | .2598 | .1197 | .005 |
| $LPM_1(\mu)$ | -.250 | -.1874 | -.3117 | .037 |
| $LPM_2(\mu)$ | -.221 | -.2929 | -.1499 | .003 |
| skewness | .201 | .2907 | .1113 | .000 |
| standard deviation | -.1560 | -.0848 | -.2273 | .016 |

The comparison of correlation coefficients for $LPM_x(100)$ and $LPM_x(\mu)$, (x = 0, 1, 2), shows that LPMs with 100 as target have higher values. The difference between the correlation coefficients for LPMs of the same order but with different targets is significant ($\alpha < 0.01$) throughout. The $LPM_0(100)$ shows the highest correlation to individual ratings for both framings. This means that people's risk perception is influenced to a considerable degree by the probability of loss where a loss is defined by the starting price of 100. Furthermore, the $LPM_2(100)$ explains risk ratings significantly ($\alpha < 0.0001$) better than the standard deviation does. However, the difference between $LPM_2(\mu)$ and the standard deviation in explaining subjects' ratings is not significant. This result confirms that hypothesis 2 is at least tentatively confirmed, i. e. the mean is not the appropriate target outcome determine the risk perception for most of the distributions used in this study.

Average correlation coefficients between symmetrical risk measures and individual risk ratings unanimously show a negative sign. Table 3 only presents the coefficients for the standard deviation because the results for other symmetrical measures are basically identical. The negative sign indicates that positive deviations from the individual target outcome lead to a reduction of perceived risk. This feature is one of the assumptions underlying the risk function proposed by Franke/Weber (1997, p. 10) and is not captured by LPMs. The risk reducing impact of positive deviations from the starting price 100 is further stressed by the negative signs of $LPM_x(\mu)$, $(x = 1, 2)$.

The risk ordering of the eight stocks does not change if one increases the weighting coefficient of the LPM that is used to rank the alternatives. Therefore, hypothesis 3, stating a closer correspondence of risk ratings with LPMs of higher order, can only be tested by using correlation coefficients. As shown above, the highest correlation is found for the probability of loss, i. e. the $LPM_0(100)$, but also the expected loss, i. e. the $LPM_1(100)$, shows a strong correspondence to risk ratings. The correlation for the $LPM_1(100)$ is the same for both framings. The higher coefficient for the $LPM_2(100)$ in the chart group hints to an increased relative importance of negative deviations for this group while the histogram framing may lead subjects to consider other characteristics of the distributions as well.

Table 3 shows that the difference between the two framings is more pronounced for the $LPM_x(\mu)$. This result implies that the mean is easier to detect in the histogram framing and therefore this target is used more often intuitively in risk judgments. Interestingly, the correlation for the $LPM_1(\mu)$ is higher (stronger negative) in the chart framing while the $LPM_2(\mu)$ is higher in the histogram framing. This result is astonishing because the mean of a distribution should be more easily discernable in the histogram framing since the anchoring effect of the starting price is weaker. On the other hand, it is not surprising that the correlation coefficient for skewness is a lot higher when stocks are displayed as histograms. The really puzzling result is that for both framings risk perception increases with skewness. This implies a preference for negative skewness and contradicts the majority of empirical findings in studies of financial decision making. However, it has to be considered, that if the mean is not important for subjects' ratings (see table 3), skewness is neither since its definition depends on the mean.

Hypothesis 4 about the effects of framing has partially been tested and interpreted in connection with the other hypotheses. As the short discussion (see above) on the impact of presentation modes already showed the histogram framing leads to higher risk ratings for most of the stocks as long as there is a significant difference between the stocks. Only for stocks 5 and 8 perceived risk is higher in the chart framing.

If one takes the risk ratings on a within-subjects basis the framing results are slightly different. The subjects rated four stocks each in the histogram and in the chart frame but with different levels of mean in each of the four groups. Due to this design feature a within-comparison of framing effects is superimposed by the effect of different means. Since the starting price of 100 is overwhelmingly used as target outcome this results in a higher positive deviations for stocks with a mean of approximately 120. As has already been argued, the consequence is a lower perceived risk. Therefore, for the subjects that judged the stocks with mean 100 in the chart framing the subjective risk is higher than that for the stocks in the histogram framing (with a mean of 120). For the other half we get the opposite result, i. e. stocks in the histogram framing (now with mean 100) are judged riskier than the stocks displayed as charts (mean 120). Although the data does not permit to support this finding by means of an ANOVA the contention that reference point effects are stronger than information display effects seems justified.

**General discussion**

The experimental study explored the notion of risk and tried to relate different risk conceptions to individual risk perception. The results strongly dismiss symmetrical risk measures like the standard deviation in favour of asymmetrical measures that capture the notion of risk as negative deviations from a point of reference to a much higher extent. There has been a lot of intuitive reasoning in favour of asymmetrical risk measures and a substantial number of studies that use lotteries to demonstrate the importance of shortfall risk. This experimental investigation demonstrates this important characteristic of risk perception in a financial context by using subjects that most probably resemble typical private investors.

After showing that asymmetrical risk measures like the class of LPMs are suitable for reflecting people's risk perception, the question occurred which reference point is most likely used by subjects in defining losses. A comparison of risk ratings for the eight stocks and the analysis of correlation coefficients between individual ratings and theoretical risk measures showed that a very strong status quo or anchoring effect influenced subjects to employ the starting price of 100 in defining risk instead of the mean. Although it is hardly possible to specify an individual's exact reference point or adaptation level on a theoretical basis this result underlines at least the necessity of flexible risk measures and risk-value-models.

The second important question in defining a particular LPM is the order of the weighting coefficient which determines the magnitude of large deviations compared to small deviations from the reference point. Although theoretical and empirical arguments would favour an order of two or higher implying that the investor is decreasingly risk averse or shows at least a preference for positive skewness the results do not support this claim. Surprisingly, the $LPM_0(100)$ which gives the shortfall probability from the starting price 100 is the measure that explains individual risk ratings best. It is followed by the $LPM_1(100)$ that represents the expected loss in the sense of negative deviations from the price of 100. It seems as if subjects are mainly concerned with the danger of losing money compared to the initial investment. Perhaps, this behavior can be explained (although the data do not allow a closer examination of this issue) with a lexicographic decision rule that first eliminates alternatives that fall below a particular target level and subsequently compares the remaining alternatives on other attributes. The notion of risk as the probability of loss has been proposed on axiomatic grounds by Fishburn (1984). The concentration on probability of loss was also found in early empirical studies on financial and managerial decision making (Laughhun/Payne/Crum (1980); Mao/Helliwell (1969)).

Another surprising finding is the negative sign of correlation coefficients for symmetrical risk measures and for most of the LPMs with the mean as target outcome. The observation that positive deviations from the target outcome (the starting price of 100 for the majority of subjects) reduce perceived risk corresponds to the risk function proposed by Franke/Weber (1997, p. 10). This means that positive deviations are not irrelevant as sometimes proposed in the literature on decision theory (Fishburn 1982) but instead decrease perceived risk.

Even though a very broad conception of the term framing was used in this context (only information presentation was manipulated directly but not the reference points) the results show the importance of how the stocks are represented. Stochastic dominance relations between the stocks are rather detected in the histogram framing than in the chart framing. The former presentation mode should therefore be preferred when investors are provided with information about risky investments. However, in practice, investment advisers very often supply their clients with charts of price distributions or with statistical measures which the clients cannot interpret properly.

The above mentioned results can only be considered as a first step in the analysis of individual investors' risk perception. The methodology and the stimuli used were rather simple and have to be exposed to closer analysis of risk behavior in the future. The appropriateness of LPMs or other risk measures could be tested in more detail with probit models which require a substantial number of individual risk comparisons between alternatives. Verbal protocols or other methods suitable for the analysis of information processing of investors should be used to verify the results. Individual differences in risk attitude and other personality traits related to financial decision making like locus of control or cognitive style may also be taken into account.
Finally, the potential limitations of using students as subjects and of not granting financial incentives have to be acknowledged. Control experiments are definitely needed to test the implicit assumption in this study that the results would not have been significantly different if more representative subjects (actual shareholders and investment professionals) and financial incentives had been used.

# 4 Conclusions and Directions for Future Research

The superiority of asymmetrical risk measures has been clearly demonstrated. The continued development of portfolio selection algorithms based on this interpretation of risk is surely the right direction for future research. The construction of equilibrium asset pricing models necessarily entails homogenous expectations. This assumption may be justified considering the market impact of large institutional investors and their similar expectations and risk notions. However, this requirement stands in sharp contrast to the rich nature of the risk concept which instead makes flexible risk-value models inevitable. It is premature to advocate a particular risk measure on the basis of the experimental results. However the findings give directions for future theoretical research.

Risk perception is not only a theoretical issue but also forms the basis for costumer oriented financial services strategies. If financial institutions understand their customers' needs and the way they use the information given they are able to fulfill their needs and satisfy their customers. The results from this study can help financial advisers to give appropriate information to their clients.

The dominance of the probability of loss over the other LPMs has an interesting implication for corporate risk management, too. The probability of loss lies at the heart of value-at-risk models.[1] Although violations of the principles of expected utility theory are possible when risk averse investors use the value-at-risk to decide between risky alternatives (Guthoff/Pfingsten/Wolf 1997), this risk measure seems to represent to a large extent people's understanding of risk. If one does not want to dismiss expected utility as the norm of rational behavior managers have to be trained to recognize risk in a way that guarantees optimal decisions.

Some problems remain: Risk perception, risk attitude and risk taking have to be considered and measured separately. The separation of these three concepts is often neglected in the literature but the first promising results in examining these issues separately justifies further research (Weber/Milliman 1997; Sitkin/Weingart 1995). The formation of aspiration levels in financial decision making (as well as in other contexts) is also still an open question that has to be addressed by future research.

1 Note that $LPM_0$ and the most widely used risk measure in practice, the value-at-risk, are related the following way: $LPM_0 = F(VaR)$, where F is the cumulative distribution.

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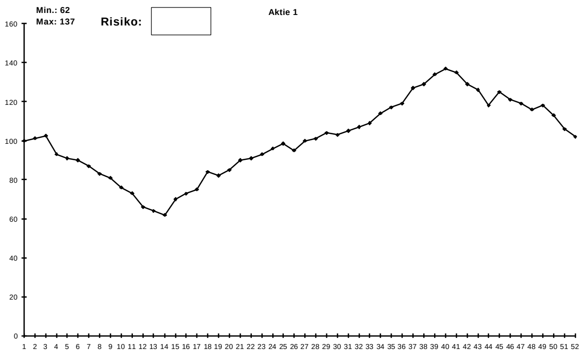
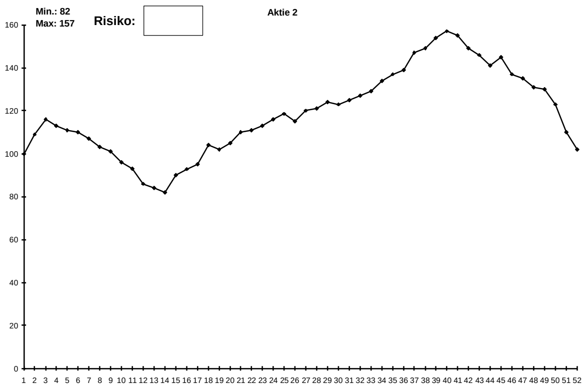
# APPENDICES

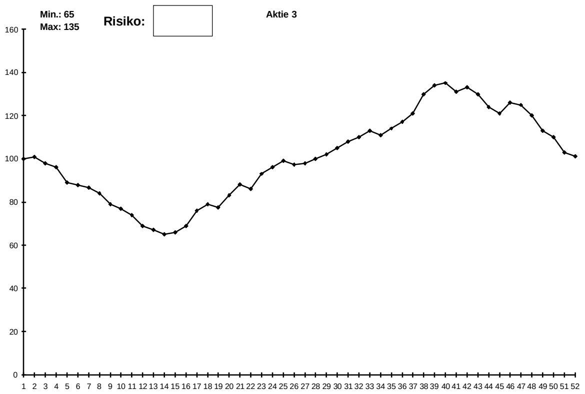
## Appendix 1a: Price distributions of the stocks

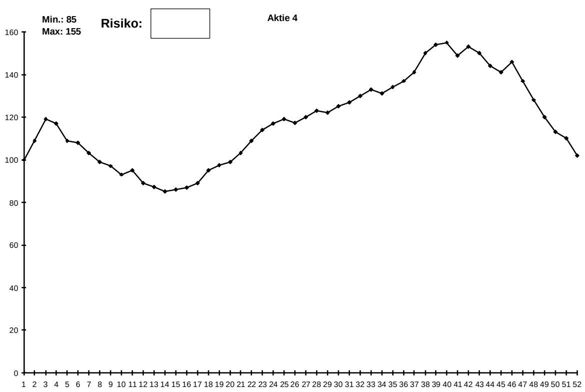
| Week | Stock 1 | Stock 2 | Stock 3 | Stock 4 | Stock 5 | Stock 6 | Stock 7 | Stock 8 |
|---|---|---|---|---|---|---|---|---|
| 1 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| 2 | 101 | 109 | 101 | 109 | 93 | 108 | 91 | 111 |
| 3 | 102 | 116 | 98 | 119 | 85 | 111 | 93 | 113 |
| 4 | 93 | 113 | 96 | 117 | 90 | 110 | 97 | 117 |
| 5 | 91 | 111 | 89 | 109 | 84 | 104 | 87 | 115 |
| 6 | 90 | 110 | 87 | 107 | 80 | 100 | 89 | 119 |
| 7 | 87 | 107 | 86 | 103 | 73 | 93 | 88 | 109 |
| 8 | 83 | 103 | 84 | 99 | 70 | 90 | 85 | 108 |
| 9 | 81 | 101 | 79 | 97 | 65 | 85 | 83 | 105 |
| 10 | 76 | 96 | 76 | 93 | 63 | 83 | 86 | 107 |
| 11 | 73 | 93 | 74 | 95 | 61 | 81 | 79 | 99 |
| 12 | 66 | 86 | 69 | 89 | 60 | 80 | 76 | 96 |
| 13 | 64 | 84 | 67 | 87 | 62 | 82 | 75 | 95 |
| 14 | 62 | 82 | 65 | 85 | 71 | 91 | 74 | 94 |
| 15 | 70 | 90 | 66 | 86 | 70 | 90 | 65 | 85 |
| 16 | 72 | 92 | 69 | 87 | 82 | 102 | 63 | 83 |
| 17 | 75 | 95 | 76 | 89 | 92 | 112 | 70 | 90 |
| 18 | 84 | 104 | 79 | 95 | 100 | 120 | 77 | 97 |
| 19 | 82 | 102 | 77 | 97 | 102 | 122 | 79 | 99 |
| 20 | 85 | 105 | 83 | 99 | 105 | 125 | 78 | 98 |
| 21 | 90 | 110 | 88 | 103 | 107 | 127 | 86 | 106 |
| 22 | 91 | 111 | 86 | 109 | 104 | 124 | 87 | 107 |
| 23 | 93 | 113 | 93 | 114 | 102 | 122 | 84 | 104 |
| 24 | 96 | 116 | 96 | 117 | 112 | 132 | 86 | 106 |
| 25 | 98 | 118 | 99 | 119 | 110 | 130 | 89 | 109 |
| 26 | 95 | 115 | 97 | 117 | 115 | 135 | 96 | 116 |
| 27 | 100 | 120 | 98 | 120 | 120 | 140 | 97 | 117 |
| 28 | 101 | 121 | 100 | 123 | 123 | 143 | 95 | 115 |
| 29 | 104 | 124 | 102 | 122 | 113 | 133 | 99 | 119 |
| 30 | 103 | 123 | 105 | 125 | 110 | 131 | 98 | 118 |
| 31 | 105 | 125 | 108 | 127 | 109 | 130 | 96 | 116 |
| 32 | 107 | 127 | 110 | 130 | 120 | 140 | 99 | 128 |
| 33 | 109 | 129 | 113 | 133 | 123 | 143 | 101 | 139 |
| 34 | 114 | 134 | 111 | 131 | 125 | 145 | 98 | 146 |
| 35 | 117 | 137 | 114 | 134 | 129 | 149 | 110 | 149 |
| 36 | 119 | 139 | 117 | 137 | 123 | 143 | 118 | 156 |
| 37 | 127 | 147 | 121 | 141 | 121 | 141 | 127 | 159 |
| 38 | 129 | 149 | 130 | 150 | 122 | 142 | 135 | 158 |
| 39 | 134 | 154 | 134 | 154 | 120 | 140 | 139 | 159 |
| 40 | 137 | 157 | 135 | 155 | 114 | 134 | 137 | 149 |
| 41 | 135 | 155 | 131 | 149 | 117 | 137 | 139 | 145 |
| 42 | 129 | 149 | 133 | 153 | 123 | 143 | 129 | 147 |
| 43 | 126 | 146 | 130 | 150 | 117 | 137 | 127 | 138 |
| 44 | 118 | 141 | 124 | 144 | 114 | 134 | 124 | 135 |
| 45 | 125 | 145 | 121 | 141 | 110 | 130 | 118 | 129 |
| 46 | 121 | 137 | 126 | 146 | 113 | 133 | 115 | 137 |
| 47 | 119 | 135 | 125 | 137 | 108 | 128 | 113 | 133 |
| 48 | 116 | 131 | 120 | 128 | 110 | 130 | 117 | 127 |
| 49 | 118 | 130 | 113 | 120 | 107 | 127 | 112 | 121 |
| 50 | 113 | 123 | 110 | 113 | 103 | 117 | 105 | 113 |
| 51 | 106 | 110 | 103 | 110 | 101 | 110 | 103 | 109 |
| 52 | 102 | 102 | 101 | 102 | 100 | 102 | 100 | 102 |

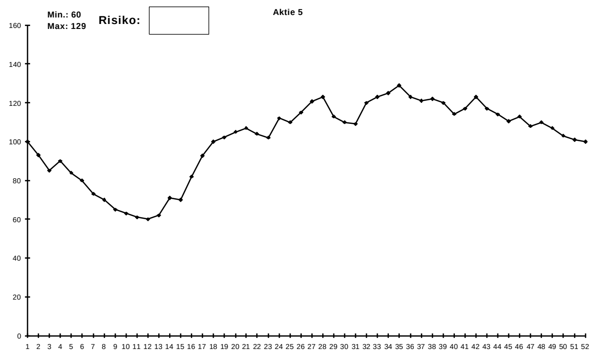
# Appendix 1b: Displays of the stocks

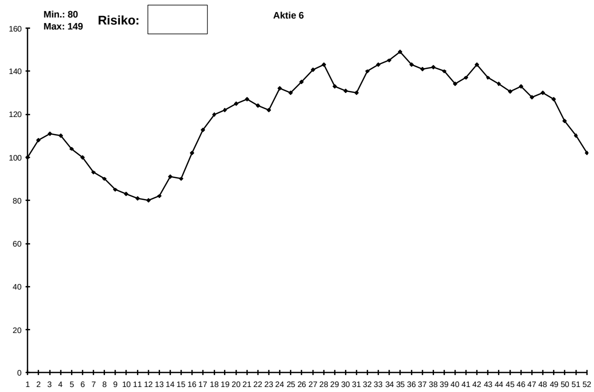


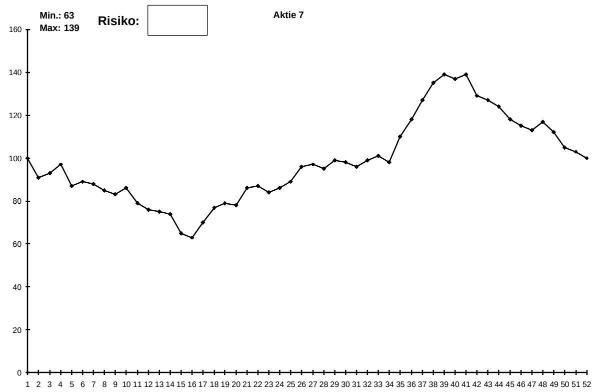



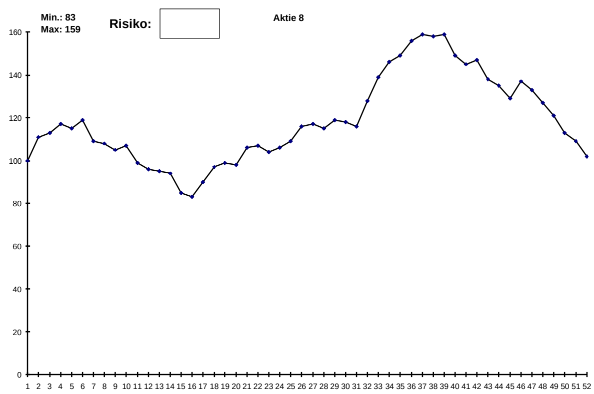



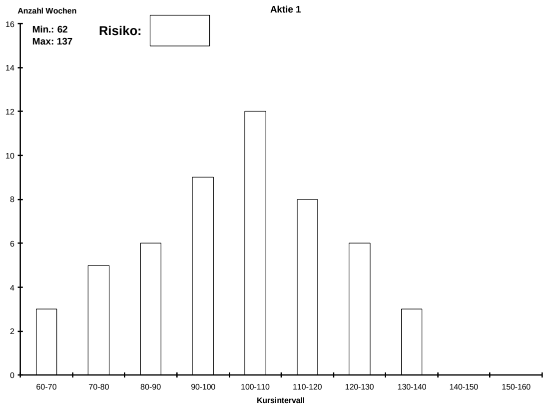



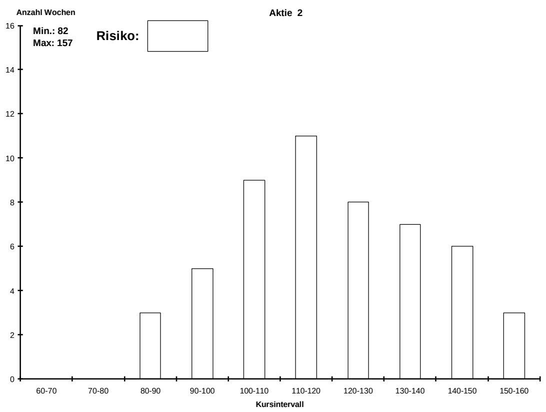



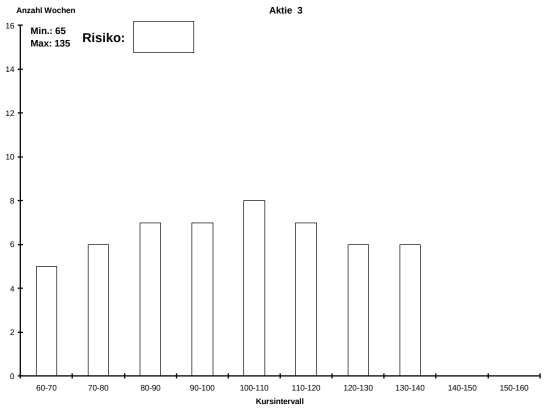



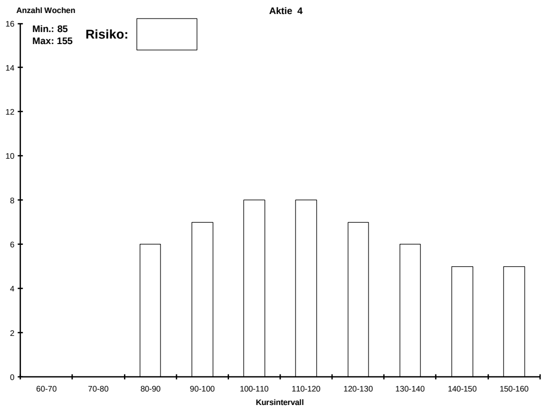



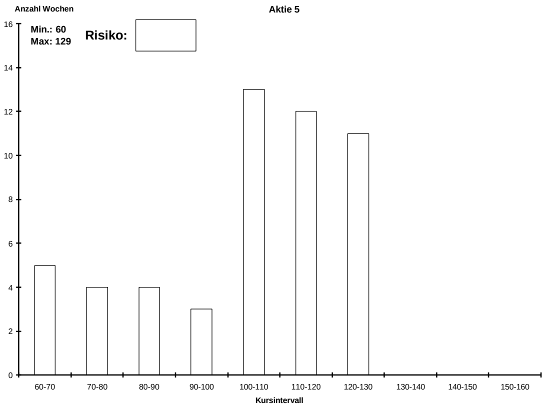



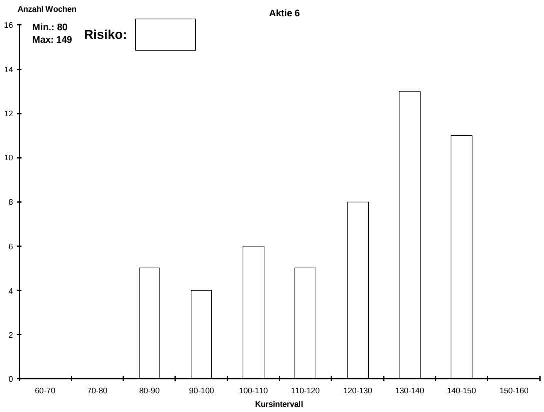

Aktie 1
Anzahl Wochen
Min.: 62
Max: 137
Risiko:
Kursintervall

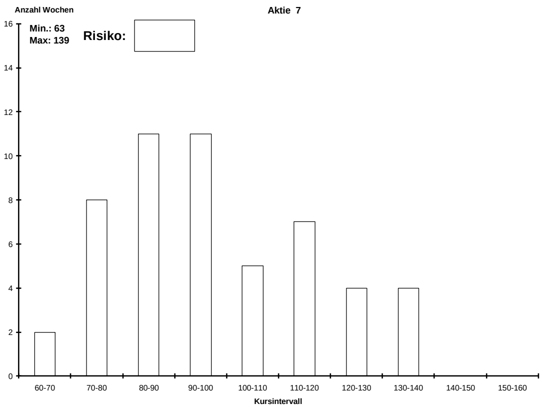

Aktie 2
Anzahl Wochen
Min.: 82
Max: 157
Risiko:
Kursintervall

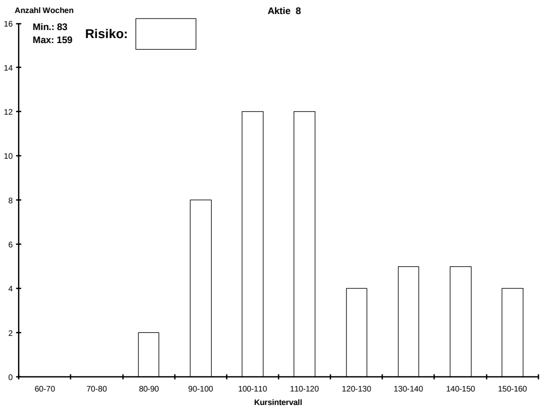

Aktie 3
Anzahl Wochen
Min.: 65
Max: 135
Risiko:
Kursintervall


Aktie 4
Anzahl Wochen
Min.: 85
Max: 155
Risiko:
Kursintervall


Aktie 5
Anzahl Wochen
Min.: 60
Max: 129
Risiko:
Kursintervall


Aktie 6
Anzahl Wochen
Min.: 80
Max: 149
Risiko:
Kursintervall


Aktie 7
Anzahl Wochen
Min.: 63
Max: 139
Risiko:
Kursintervall


Aktie 8
Anzahl Wochen
Min.: 83
Max: 159
Risiko:
Kursintervall

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## Appendix 1c: characteristics of the distributions for the eight stocks.

| | Stock 1 | Stock 2 | Stock 3 | Stock 4 | Stock 5 | Stock 6 | Stock 7 | Stock 8 |
|---|---|---|---|---|---|---|---|---|
| **distribution** | normal | normal | uniform | uniform | negative skew | negative skew | positive skew | positive skew |
| **risk measure** | | | | | | | | |
| **$LPM_0(100)$** | 0.44 | 0.15 | 0.48 | 0.25 | 0.31 | 0.17 | 0.62 | 0.19 |
| **$LPM_1(100)$** | 7.72 | 1.56 | 8.07 | 1.95 | 7.66 | 2.40 | 8.75 | 1.23 |
| **$LPM_2(100)$** | 184.42 | 19.57 | 192.06 | 21.44 | 229.52 | 37.10 | 183.90 | 13.58 |
| **$LPM_0(\mu)$** | 0.48 | 0.54 | 0.52 | 0.52 | 0.38 | 0.40 | 0.58 | 0.62 |
| **$LPM_1(\mu)$** | 8.06 | 8.25 | 8.26 | 8.59 | 8.05 | 8.65 | 7.76 | 8.21 |
| **$LPM_2(\mu)$** | 195.40 | 180.89 | 197.94 | 195.09 | 246.22 | 245.69 | 156.63 | 162.59 |
| **mean** | 100.70 | 118.72 | 100.36 | 117.65 | 101.06 | 120.06 | 98.35 | 118.31 |
| **standard dev.** | 19.60 | 19.68 | 19.91 | 20.41 | 19.62 | 20.04 | 19.39 | 20.05 |
| **mad-μ*** | 16.12 | 16.49 | 16.51 | 17.18 | 16.10 | 17.29 | 15.51 | 16.42 |
| **min. price** | 62.00 | 82.00 | 65.00 | 85.00 | 60.00 | 80.00 | 63.00 | 83.00 |
| **max. price** | 137.00 | 157.00 | 135.00 | 155.00 | 129.00 | 149.00 | 139.00 | 159.00 |
| **skewness** | -0.07 | 0.16 | 0.00 | 0.19 | -0.77 | -0.60 | 0.47 | 0.50 |

*) mad = mean absolute deviation from the mean.

## Appendix 2: Cumulative distributions for the eight stocks