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Characterizing Risk Attitudes of Industrial Managers

by

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Abstract. We study the risk attitudes of an important segment of the economy: managers. We conduct artefactual field experiments with 130 managers from 12 industrial companies. Our analysis is particularly careful to evaluate alternative models of decision-making under risk. In general, we find that the managers in our sample are moderately risk averse. Assuming a standard EUT model they exhibit similar risk attitudes as other sample populations. However, we find some differences within our sample. Superiors exhibit a higher level of risk aversion than team members that work for them in their department. Comparing purchasing managers with a random sample of non-purchasing managers from different corporate functions such as controlling, sales, engineering and so on, we cannot conclude that they differ from each other. We show that alternative theories of risky behavior provide complementary information on the risk attitude of industrial managers. While an expected utility theory model only characterizes managers as globally risk averse, we learn from a prospect theory model that the managers in our sample are only risk averse for a certain range of payoffs. For other payoffs, they even exhibit risk-seeking behavior. The reference point that determines which outcomes are to be viewed as losses and which as gains is not that induced by the task frame. We show that subjects had implicit expectations about their earning in the experiment, and used these expectations to evaluate the lotteries presented to them. Remarkably, the managers in our sample did not weigh probabilities and they did *not* exhibit a hypothetical bias in their decisions.

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1. Introduction

Experimental procedures to elicit risk preferences have been applied to study risk attitudes of subjects in laboratory environments and in the field. The main focus of the laboratory studies have been university students, but many of the field experiments have started to consider the attitudes of target populations. We provide a comprehensive characterization of the risk attitudes of actual industrial managers. We use data obtained from an artefactual field experiment involving 130 managers from 12 industrial companies in Germany, Austria and Switzerland. The risk attitudes of industrial managers are of particular interest because they routinely make risk management decisions that involve significant stakes.

Industrial managers represent a relatively homogenous group of subjects. Middle and upper management are predominantly male and have degrees in engineering or business administration. Moreover, industrial managers are a self-selected group of individuals with similar professional interests in specific managerial tasks, and routinely face situations in which they have to decide over risky prospects. For instance, a large fraction of the managers in our sample are industrial purchasing managers. Typically, purchasing managers have to assess suppliers based on a trade-off between purchasing price, product quality and the potential risks of supplier failure. Their company's exposure to supply risks is determined in large measure by their choices over the number of suppliers to work with, particular sourcing regions, and purchasing volumes for individual suppliers. These characteristics of industrial managers prompt the question whether this group exhibits the same level of risk aversion as other subject groups. Our first research questions are therefore what risk attitudes industrial managers exhibit in an artefactual field experiment, and whether those risk attitudes differ from other subjects.

Even within a group of managers, we may anticipate different latent decision making processes depending on managers' corporate functions and their specific positions in a company's hierarchy. For example, managers that have chosen to work in the area of operations or accounting are perhaps more exposed to decision making problems under risk and are more focused on quantitative and analytical approaches than managers in the marketing or sales departments. Thus, even within a single company, one might find a strong self-selection, and it is not obvious whether the risk attitudes of managers vary across different corporate functions. It is also conceivable that risk attitudes differ depending on the hierarchical level of the manager. For example, subjects that belong to upper management are more often confronted with decisions under risk that involve larger stakes. In our sample we have a significant number of purchasing managers and randomly picked managers from other departments that are on a similar hierarchical level. We analyze whether purchasing managers and other managers exhibit different risk attitudes. In addition, for the group of purchasing managers we obtained data from both superiors and team members and analyzed potential differences in their risk attitudes. The composition of our sample thus allows us to ask if the risk attitudes of superiors differ from the risk attitudes of team members, and whether the risk attitudes of industrial managers vary across different corporate functions.

A final characteristic of managers is that a myriad of decision models and tools have been developed to support their day-to-day decision making. However, most of these tools make restrictive assumptions about the risk attitudes of the decision makers they are designed to support. For example, decision models often assume, implicitly or explicitly, that decision makers are risk neutral. Yet Kliger and Levy (2009) show, for example, that it is not appropriate to characterize financial investors as risk neutral. Once we recognize that managers are not risk neutral, hoiwever, there are many alternative ways to structurally model decision making behavior. Popular decision making theories in this context are Expected Utility Theory (EUT), Rank-dependent Utility Theory (RDU) and Prospect Theory (PT). However, these competing decision theories often result in different model specifications and may lead to contradicting recommendations. Since limited empirical evidence exists that could guide researchers when developing decision models for the use of industrial managers, it is not surprising that one finds proponents of each theory in the literature. For example, in the field of operations and inventory management, Eeckhoudt et al. (1995) and Agrawal and Seshadri (2000) both utilize an EUT model. By contrast, when analyzing their experimental data in a supply chain context, Schweitzer and Cachon (2000) primarily employ a PT model. Therefore, we aim to analyze and contrast different decision theories under risk.

Looking at a specific decision theory such as RDU or PT, it is not obvious that we should find similar structural results for industrial managers as for other subjects as students, workers or broader population samples. For example, researchers found out that some subjects transform objective probabilities presented to them in experiments into subjective decision weights (e.g. Bleichrodt and Pinto, 2000). Such subjects tend to over-weight or under-weight probabilities depending on the rank of the prize. Given that most industrial managers have an engineering or business background, they most likely have a sound education in statistics and are familiar with the concept of probabilities. Moreover, they are also used to work with probabilities in their day-to-day business. Popular management concepts like *Six Sigma*[1] heavily rely on statistical concepts and (objective) probabilities. Therefore, it is not clear that managers also weigh probabilities in the same manner as students (Bleichrodt and Pinto, 2002) or people in developing countries that are less familiar with the concept and assessment of probabilities (Harrison et al., 2009). This leads us to ask what insights on the risk attitudes of industrial managers can we get from characterizing their behavior using the decision theories EUT, RDU and PT?

In the past researchers have gained structural insights on the decision making of managers by considering hypothetical questions. However, it is not obvious that these structural insights are reliable measures of motivated behavior: there is considerable evidence of differences in behavior under risk when one considers hypothetical choices (e.g. Holt and Laury, 2002/2005). However, unlike other groups of subjects, managers are used to working with hypothetical scenarios. Management tools such as *Scenario Planning*[2] are very common (van Notten, 2006). The managers

[1] The Six Sigma methodology is used by companies to identify and remove causes of defects and errors in manufacturing and business processes to get as close as possible to "zero defects". To achieve Six Sigma quality, a process must produce no more than 3.4 defects per million outputs (e.g. parts). The Six Sigma methodology uses, for example, statistical methods like decision trees, regression and correlation analyses and analysis of variance (ANOVA)

[2] Scenario planning is a management tool to deal with uncertain changes in the market conditions (e.g. new regulations, behaviors of competitors, new innovations and so on). In the scenario planning process managers consider different scenarios of plausible futures and aim to make management decisions that are sound for all plausible futures.

who use such tools are arguably familiar with the evaluation of different hypothetical situations. Thus it might not be appropriate to assume that managers are subject to the same decision bias. This leads us to our final research question: do industrial managers exhibit differences in behavior in hypothetical and real settings?

In Section 2 we describe the design of our experiment and the basic procedures used for eliciting risk preferences. Section 3 outlines the three popular decision theories under risk mentioned above, and the estimation procedures we use to infer subjects' risk attitudes from binary lottery choices. Section 4 gives the results of our analysis: we describe the risk attitudes of the managers in our sample and address each of the research questions posed above. In Section 5 we relate our results to the literature. Section 6 summarizes our results.

2. Experimental Design

2.1 Sample

Our sample consists of 130 managers from 12 industrial companies in Germany, Austria and Switzerland. The companies have an average turnover of EUR 11.2 billion per annum, ranging from a minimum of EUR 100 million to a maximum of EUR 60 billion. They represent a wide range of industries, including aviation, power generation, mechanical engineering, aerospace, logistics and construction.

Subjects were aged between 20 and 64, with an average age of 39.3. Approximately 70% were male. Some 72% had an undergraduate or post-graduate degree, most commonly in business or engineering; the remaining 28% had only undergone professional training. The managers fulfilled different functions in their companies, as shown in Table 1.

Table 1. Corporate functions of recruited managers

Function	Number of managers	Function	Number of managers
Strategic Purchasing	92	Information Technology	4
Corporate Strategy	6	Human Resources	4
Marketing & Sales	6	Finance & Controlling	4
General Management	6	Service & Support	3
Engineering/R&D	4	Administration	1

Table 1 shows that 92 of the 130 subjects were strategic *purchasing managers*, while 38 were *non-purchasing managers* working in other functions. Of the 92 purchasing managers, 80 were team members or team leaders, and we refer to this group as *buyers*. The remaining 12 purchasing managers were their *superiors*, and we refer to them as such. At least 4 purchasing managers (3 buyers and their superior) from each company participated in the experiment. The managers in the sample had substantial professional experience: on average they had worked in industry for 18 years.

2.2 Conduct of sessions

The experiment was conducted in 25 sessions that took place at the companies' premises, using a printed questionnaire. Sessions involved no more than eight subjects and were held in a suitable meeting room. At the beginning of each session, an experimenter gave a short introduction informing subjects of the general purpose of the study. Subjects then picked a questionnaire on a random basis, so that we allocated them to the different treatments and task orders.

The questionnaire reproduced in the Appendix contained all the instructions required by participants. No additional verbal instructions were provided unless there were specific questions. The first part of each questionnaire asked for demographic data (e.g., age, marital status, education, income), job-specific information (e.g., department, position, experience) and details of the company (e.g., industry, turnover). The following two parts of the questionnaire presented the decision tasks. In addition to the task used to generate the results presented here, we asked subjects to complete two complementary tasks (henceforth Task A and Task B, not discussed here[3]). Subjects were asked to leave the room when they had completed all three parts of the questionnaire. Cash payments were privately made in a separate room. The average earnings across all sessions was EUR 31 per subject, and the average duration of the experiment was 60 minutes.

2.3 Basic elicitation procedure

We employed a *Random Lottery Pair* (RLP) design following Hey and Orme (1994), to elicit participants' risk preferences. Harrison and Rutström (2008) review different elicitation procedures, and argue that this design makes very few assumptions about behavior and framing effects. We simply asked subjects to make direct preference choices over 30 pairs of lotteries. To create incentives for truthful responses, one of the choices was chosen at random for payout at the end of the experiment. Each of the 30 choices was made between two lotteries, called Lottery A and Lottery B. The two lotteries were presented to the subjects as pie charts. The pie charts showed the lottery prizes and the corresponding probabilities. Our study framed the potential outcomes of the lotteries as losses. Subjects received an initial endowment of EUR 40 from which they had to pay for any losses incurred during the experiment.

Figure 1 gives an example of a binary choice in this loss frame. In this instance, subjects can lose EUR 7, 14 or 20 of their endowment in Lottery A with probabilities of 0.70, 0.15 and 0.15, respectively. In Lottery B they can lose EUR 7 or 14 with probabilities of 0.30 and 0.70, respectively. Each individual lottery was generated by choosing two or three different prizes from a set of six fixed prizes: EUR 0, -7, -14, -20, -28 and -40. All lotteries are defined in an appendix.

[3] Task A was similar to the task that we present in this paper but the subjects did not bear the consequences of their decisions themselves. In Task B subjects made similar decisions as in Task A but in a supply chain context.

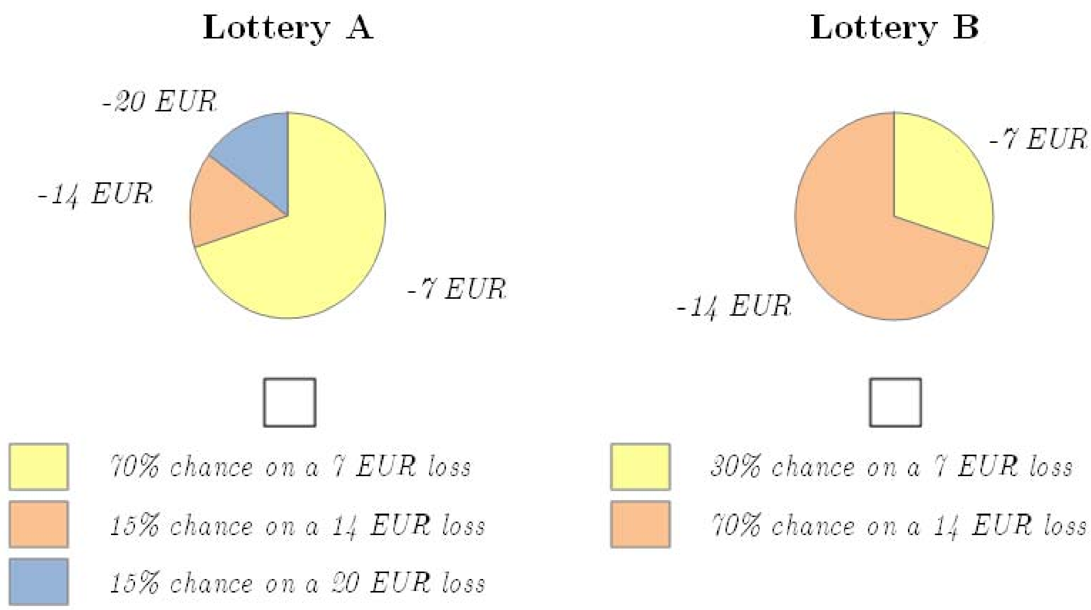

Fig 1. Sample display shown to subjects

We choose to work with a loss frame and an initial endowment because this setting is a more natural representation of the field context in which most managers in our sample make decisions over uncertain prospects. The majority of our managers are purchasing managers that will typically work with a purchasing budget. Their decisions in terms of selecting and contracting suppliers determine how much of this budget is actually spent. If, for example, a purchasing manager decides to contract the one supplier that offers the lowest purchasing price, he might save some money compared to his purchasing budget. However, his company might be exposed to greater risk in case of delivery failures of this suppliers. If he contracts more than one supplier for the same input material (so-called multiple sourcing), he might spend more of his purchasing budget as he cannot fully leverage economies of scale but he reduces at the same time his companies' exposure to disruption to supply.

We informed subjects that one of their 30 choices would be chosen randomly for payout, and this was done by throwing a thirty-sided die. The subject's preferences over that pair of lotteries were applied and a 100-sided die was thrown to play out the selected lottery for actual payment. The resulting loss of between EUR 0 and 40 was then deducted from the initial endowment of EUR 40.

Although we cannot use the responses to the RLP design to directly elicit risk attitudes from subjects' choices, we can use it to estimate utility functionals over lotteries for individuals, as explained later.

2.4 Tasks and treatments

In our experiment we varied the tasks and treatments for different groups of participants. This was done with two main objectives. First, we sought answers to the research questions posed in Section 1. Second, we wanted to control for the treatment effects previously identified in similar experimental settings. Figure 2 provides an overview of the individual tasks and treatments.

The non-purchasing managers and superiors performed the task outlined above with real payments. In the case of buyers, however, we introduced two modifications. First, we conducted the experiment with both real and hypothetical payments. Second, we varied the order of the tasks.

Real and hypothetical payments. Holt and Laury (2002, 2005) provide strong evidence that subjects are significantly less risk averse when they are confronted with hypothetical payoffs than if real payments are involved. To explore this bias, we conducted the experiment with both real and hypothetical payments for buyers. In each session, approximately half of the subjects did the experiment with real payments and half did the experiment with hypothetical payments. Subjects were randomly assigned to one of the two groups at the beginning of each session. Subjects who performed the experiment with real payments received an initial endowment of EUR 40; any amount that they lost in the experiment was ultimately deducted from that EUR 40. Subjects who performed the experiment with hypothetical payments received a hypothetical endowment of EUR 40 and did not win or lose any real money. However, they received a fixed payment of EUR 20 for participating in the experiment.

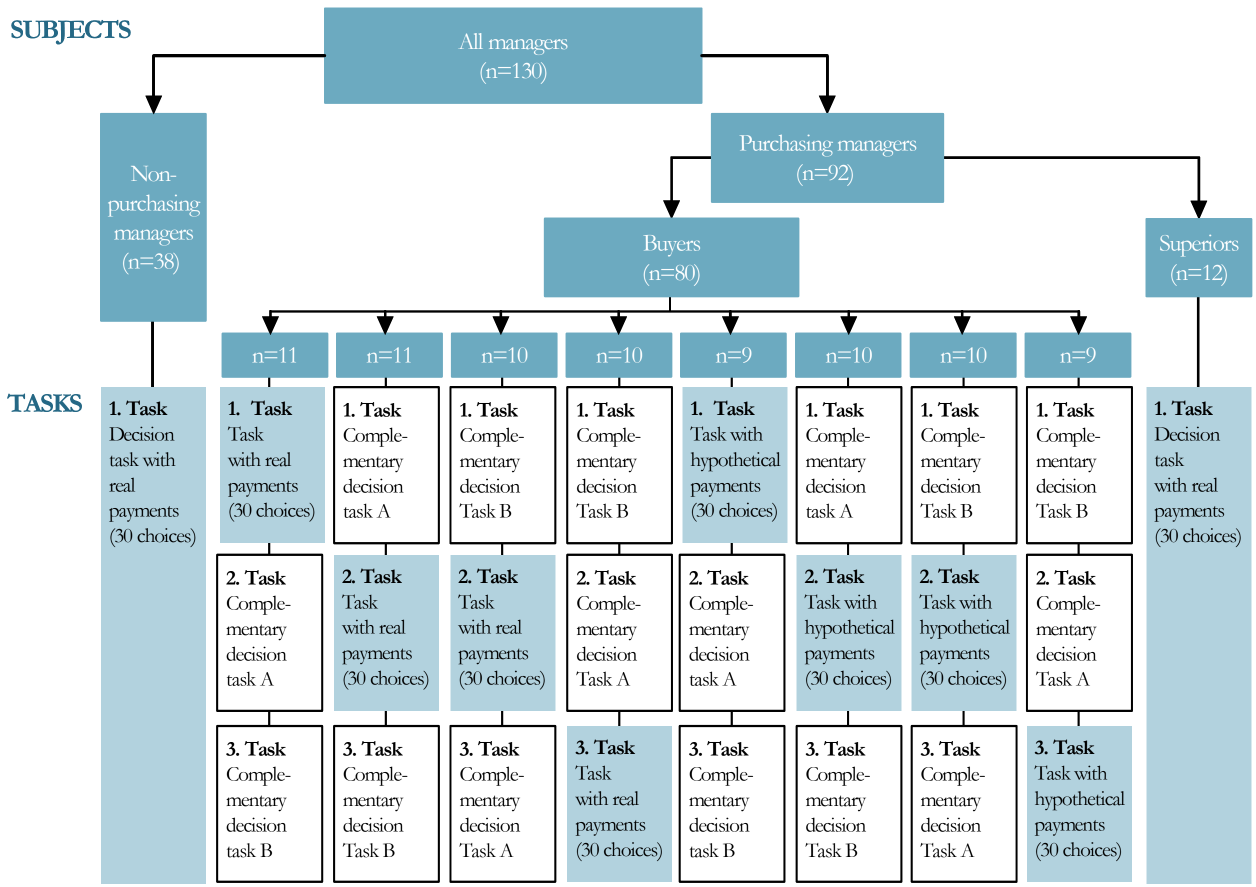

Figure 2: Experimental Design

Table 2. Different task orders used in the experiment

Order	1. Task	2. Task	3. Task
1	Task studied here	Complementary task A	Complementary task B
2	Complementary task A	Task studied here	Complementary task B
3	Complementary task B	Task studied here	Complementary task A
4	Complementary task B	Complementary task A	Task studied here

Task order. Each buyer had to complete three separate tasks: the task detailed above and Tasks A and B (that are not detailed here). Harrison et al. (2005) and Holt and Laury (2005) demonstrate that an "order effect" may occur. This effect relates to the sequence in which subjects complete different tasks. To control for this potential effect, we had different groups of subjects complete the different tasks in different orders, as shown in Table 2. We randomly assigned buyers to one of the four groups, ensuring that all groups were of equal size. Superiors and non-purchasing managers only completed one task, so there was no need to control for any potential order effect with these groups.

3. Estimation Procedure

3.1 Expected Utility Theory

We first present the standard EUT model that has been widely used in the economic literature. Let the utility function be the constant relative risk aversion (CRRA) specification

$$U(e,z) = (e+z)^{1-r}/(1-r) \tag{1}$$

for $r \neq 1$, where r is the CRRA coefficient, e the initial endowment, and z the lottery prize. With this functional form $r=0$ denotes risk-neutral behavior, $r>0$ denotes risk aversion, and $r<0$ denotes risk-loving behavior. Probabilities for each outcome z_j, p_j, are those that are induced by the experimenter, so expected utility is simply the probability-weighted utility of each outcome in each lottery. The expected utility, EU, of lottery i that consists of m different prizes is

$$EU_i = \sum_{j=1,m} [\, p_j \times U(z_j,r) \,]. \tag{2}$$

We use the index ∇EU to denote the difference between the expected utility of Lottery A, denoted by EU_A, and Lottery B, denoted by EU_B:

$$\nabla EU = (EU_B - EU_A)/\mu \tag{3}$$

The μ in equation (3) is a structural noise parameter initially proposed by Fechner (1860) and popularized by Hey and Orme (1994). It allows subjects to make some errors from the perspective of a deterministic EUT model. A thorough review of different error specifications and their implications is provided by Wilcox (2008). The latent index defined by (3) can be linked to the choices of subjects using a cumulative normal distribution function $\Phi(\nabla EU)$. This probit function translates any argument into a number between 0 and 1. Thus the index ∇EU is linked to choices by specifying that Lottery B is chosen when $\Phi(\nabla EU)>1/2$.

The likelihood of the observed responses, conditional on the EUT and CRRA specifications being true, depends only on the estimate of r, μ and the observed choices. The conditional log-likelihood is

$$\ln L^{EUT}(r, \mu, y, X) = \sum_{i=1,n} [(\ln \Phi(\nabla EU)\times \mathbf{I}(y_i = 1)) + (\ln (1-\Phi(\nabla EU))\times \mathbf{I}(y_i = -1))] \qquad (4)$$

where $\mathbf{I}(\cdot)$ is the indicator function and y_i =1 (−1) denotes that Lottery B (Lottery A) is chosen in task *i*. The vector X captures individual characteristics of subjects. The parameter r is assumed to be a linear function of the individual characteristics in X. As an example, X might contain information on the marital status of subjects, which are coded as a binary variable *MARRIED* that has a value of 1 if the subject is married, and 0 otherwise. In this example, the model extends to $r = r_0 + r_1 \times$ *MARRIED*, where r_0 and r_1 are now the parameters to be estimated compared to earlier prior model, where $r = r_0$ was assumed and only r_0 estimated.

3.2 Rank-Dependent Utility Theory

One route of departure from EUT has been to allow preferences to depend on the rank of the final outcome by means of probability weighting. The idea that one could use non-linear transformations of probabilities when weighting lottery outcomes rather than non-linear transformations of lottery outcomes into utility is presented most clearly by Yaari (1987). To illustrate this, he assumes a linear utility function - in effect, ruling out any risk aversion or risk-seeking attitude from the shape of the utility function *per se*. Instead, a concave probability weighting function would imply a risk-seeking attitude and a convex probability weighting function would imply risk aversion. Thus subjects' risk aversion can be induced by the curvature of the utility function, probability weighting, or a combination of both.

Let the utility function be the CRRA specification, as before. The rank-dependent utility, RDU, of lottery *i* that consists of *m* different prizes is

$$\mathrm{RDU}_i = \textstyle\sum_{j=1,m} [\, w_j \times \mathrm{U}(z_j, r)] \tag{4}$$

where the decision weights are given by $w_j = \omega(p_j+...+p_m,\gamma) - \omega(p_{j+1}+...+p_m,\gamma)$ for j=1,...,m-1, and $w_j = \omega(p_j,\gamma)$ for $j=m$. The subscript *j* indicates outcomes ranked from the worst (j=1) to the best ($j=m$), and $\omega(p,\gamma)$ represents some probability weighing function. One popular weighting function is proposed by Tversky and Kahneman (1992). It is assumed to have well-behaved endpoints, such that $\omega(0,\gamma)=0$ and $\omega(1,\gamma)=1$, and imply weights

$$\omega(p,\gamma)=\mathrm{p}^\gamma \,/\, (\mathrm{p}^\gamma+(1\text{-}\mathrm{p})^\gamma))^\gamma \tag{5}$$

for $0<p<1$. The monotonic function $\omega(p,\gamma)$ transforms an objective probability, p, into a "weight" that is applied when evaluating a lottery. Assuming $\gamma<1$ leads to the typical inverse S-shaped probability weighting function, which puts higher weights on lower probabilities and lower weights on larger probabilities. An alternative probability weighting function that we will also use for our subsequent analysis is the power-specification given by $\omega(p,\gamma)=p^\gamma$. Note that in the context of RDU, we refer to rank-dependent probability weighting simply as probability weighting.

The remainder of the econometric specification is the same as for EUT: the latent index is denoted by $\nabla\mathrm{RDU} = (\mathrm{RDU}_B - \mathrm{RDU}_A)/\mu$ and the probit function is given by $\Phi(\nabla\mathrm{RDU})$. The conditional log-likelihood is

$$\ln \mathrm{L}^{\mathrm{RDU}}(r, \gamma, \mu, \mathrm{y}, \mathrm{X}) = \textstyle\sum_{i=1,n} [(\ln \Phi(\nabla\mathrm{RDU})\times\mathbf{I}(\mathrm{y}_i = 1)) + (\ln (1-\Phi(\nabla\mathrm{RDU}))\times\mathbf{I}(\mathrm{y}_i = -1))] \tag{6}$$

where $\mathbf{I}(\cdot)$ is the indicator function and y_i =1 (−1) denotes that Lottery B (Lottery A) is chosen in task *i*. The parameters to be estimated in an RDU model are r, γ and the noise parameter μ.

3.3 Prospect Theory

Another popular alternative to EUT is the Prospect Theory (PT) initially developed by Kahneman and Tversky (1979). The original PT differs from EUT in three ways: (a) it allows for subjective probability weighting; (b) it allows for a reference point that determines which outcomes are to be viewed as losses and which as gains; and (c) it allows for loss aversion - the notion that the disutility of losses weighs more heavily than the utility of comparable gains.

In the original PT $w(p)=\omega(p)$, so the transformed probabilities are used directly to evaluate the prospective utility, PU, for lottery i that consists of m different prizes:

$$PU_i = \sum_{j=1,m} [\, \omega(p_j,\gamma) \times U(z_j,r)] \tag{7}$$

To be able to identify outcomes as gains or losses, and hence correctly evaluate utility, a reference point is needed. We denote this reference point by χ. Assuming a CRRA specification as before, the utility over gains ($z \geq \chi$) is defined as

$$U(z,\alpha) = z^{\alpha} \tag{8}$$

and the utility over losses ($z < \chi$) is defined as

$$U(z,\beta,\lambda) = -\lambda[(-z)^{\beta}] \tag{9}$$

where λ is the loss aversion parameter. λ is usually presumed to be greater than one; however, for the purposes of our analysis, we assume that λ is unconstrained.

The remainder of the econometric specification is as for EUT: the latent index is denoted by $\nabla PU = (PU_B - PU_A)/\mu$ and the probit function is given by $\Phi(\nabla PU)$. The conditional log-likelihood function is

$$\ln L^{PT}(\alpha, \beta, \lambda, \gamma, \mu, y, \mathbf{X}) = \sum_{i=1,n} [(\ln \Phi(\nabla PU) \times \mathbf{I}(y_i = 1)) + (\ln (1-\Phi(\nabla PU)) \times \mathbf{I}(y_i = -1))] \tag{10}$$

and the parameters to be estimated are α, β, λ, γ and μ.

One empirical challenges when using PT is to determine the correct reference point, since this reference point determines which outcomes are to be viewed as losses and which as gains. If the reference point is not correct, the estimated degree of loss aversion and risk aversion will not be reliable. Although Kahneman and Tversky (1979) emphasized the subjectivity and contextual nature of the reference point, most researchers still use the reference point that is induced by the task frame. Harrison and Rutström (2008) point out that this problem is less severe in the laboratory, where one can frame tasks to try to induce a certain frame. But more serious issues may arise in the field. We therefore follow the approach proposed by Harrison and Rutström (2008, pp. 95-98) and infer an implicit reference point from the lottery choices made by the subjects in our experiment. More formally, we determine the implicit reference point by solving

$$\chi = \underset{\tau}{\operatorname{argmax}} \left[\max_{\alpha, \beta, \gamma, \lambda, \mu} \ln L^{PT} (\alpha, \beta, \gamma, \lambda, \mu \,|\, \tau) \right]$$

In order to obtain χ in our analysis, we simply trace the log-likelihood value for potential reference points $\tau \in \{0,40\}$ and choose the reference point that yields the maximum log-likelihood value.

4. Results

We first show how EUT, RDU and PT provide *complementary* information about risk attitudes. Following the research questions posed in Section 1, we present for each theory a characterization of buyers which is then compared with those of superiors and non-purchasing managers. We begin by describing our results for a basic EUT model with CRRA. This gives us a global characterization of subjects' risk attitudes. We then provide estimates for the structural parameters of the RDU and PT models and show how these results allow for a more detailed decomposition of the possible sources of risk-averse or risk-seeking behavior. In the RDU model we allow preferences to depend on the rank of the final outcome by means of probability weighting. Probability weighting transforms objective probabilities into subjective decision weights. We decompose subjects' risk attitudes and provide estimates for both the curvature of the utility function (captured by the parameter *r*) and the rank-dependent probability weighting function. From this first analysis we want to assess to which extent the managers' risk attitude can be attributed to probability weighting. We then extend our analysis to account for the main characteristics of Prospect Theory: (1) a subjective reference point, which defines what subjects view as gains and what as losses, (2) different utility functions in the gain and loss domain, and (3) loss aversion, the notion that the disutility of losses may weigh more heavily than the utility of comparable gains.

In addition, we provide insights into two important effects that have previously been observed in lottery experiments, the hypothetical payment bias and the task order effect, to answer our last research question.

4.1 EUT: A global characterization of managers' risk attitudes

Table 3 gives the estimation results for the EUT model with a CRRA utility specification. We first discuss the estimates obtained for buyers and then those obtained for superiors and non-purchasing managers.

On the assumption that an EUT model and a CRRA utility function are appropriate for characterizing the behavior of the managers in our sample, we find that buyers exhibit moderate risk aversion. The corresponding CRRA coefficient *r* for the group of buyers is estimated at 0.30 (*p*-value <0.01). Comparing this result with our estimate of the CRRA coefficient for superiors yields an interesting result: with *r*=0.62, superiors exhibit a significantly higher level of risk aversion.

Table 3 EUT model with a CRRA utility specification

Subjects	Parameter	Estimate	*p*-value	Standard error	Lower 95% confidence interval	Upper 95% confidence interval
Buyers (n=42)	r	295	2	97	105	485
	μ	156	0	20	117	195
Superiors (n=12)	r	624	0	154	322	925
	μ	150	0	38	77	225
Non-purchasing managers (n=38)	r	397	0	62	275	519
	μ	105	0	11	82	129

For non-purchasing managers, we estimate the CRRA coefficient *r* at 0.40 (standard error of 0.06). This level is moderately higher than our estimate for buyers (r=0.30) and lower than our estimate for superiors.

Overall, the EUT specification indicates moderate risk aversion for all types of managers in our global task domain of EUR 0 to 40. This finding is consistent with the estimates reported by Holt and Laury (2002, 2005) and Harrison et al. (2005) for American college students. Harrison et. al (2007, 2009) also found moderate risk aversion when analyzing larger population samples from industrialized and developing countries. We obtain robust estimates of *r* across the different groups that are each significant at the 1% level. This is an interesting result, as the CRRA specification imposes a rigid functional form with only one parameter to be estimated. In the subsequent analysis we use more flexible utility specifications so as to obtain a more detailed characterization of the different sources of subjects' risk attitudes.

Some researchers find evidence of non-constant relative risk aversion (e.g. Holt and Laury, 2002; Harrison et al., 2005). Using an EUT model with an Expo-Power specification that is able to capture increasing or decreasing relative risk aversion, we do *not* find non-constant relative risk aversion when correcting for treatment effects. This finding is consistent with Harrison et al. (2007), for example, who report that CRRA is an appropriate assumption for characterizing the Danish population in their task domain. However, it may also be that we do find constant relative risk aversion because we did not scale up our payoffs by a factor of 20, 50 or even 90, as Holt and Laury (2002) did, for instance. Thus the only conclusion we can draw is that subjects exhibit constant relative risk aversion in our specific task domain.

4.2 RDU: The Impact of Probability Weighting and Rank-Dependence

We now present the results of our estimations of a RDU model based on the lottery choices of subjects in the sample. Our aim is to determine whether the moderate risk aversion that we found based on the EUT specification can partly be attributed to probability weighting. The two parameters to be estimated are *r* (for the curvature of the utility function) and γ (for the probability weighting function). Table 4 summarizes our results.

Table 4 RDU model with a CRRA utility specification

Subjects	Parameter	Estimate	*p*-value	Standard error	Lower 95% confidence interval	Upper 95% confidence interval
Buyers (n=42)	r	266	6	96	78	454
	γ	972	737	82	811	1133
	μ	157	0	19	120	195
Superiors (n=12)	r	631	0	180	279	983
	γ	1009	951	143	728	1289
	μ	150	0	38	75	225
Non-purchasing managers (n=38)	r	347	0	67	216	479
	γ	947	353	57	836	1058
	μ	107	0	11	85	130

For the group of buyers we find no evidence of probability weighting. The corresponding estimate of γ is 0.97 (p-value=0.73== on the null hypothesis that $\gamma=1$) and we cannot conclude that subjects transform objective probabilities into subjective decision weights. Moreover, the CRRA coefficient is very close to the estimate in the EUT model.

For other types of managers we find virtually the same results. The data does not provide support for probability weighting, and CRRA coefficients for both superiors and non-purchasing managers are very close to those obtained in the EUT model.

To summarize, our estimates of γ do not provide any evidence in favor of probability weighting. This finding is interesting because the conventional assumption, supported by a substantial amount of evidence (reviewed by Bleichrodt and Pinto, 2000; Gonzalez and Wu, 1999), is that $0<\gamma<1$. This implies over-weighting of small probabilities and under-weighting of large probabilities. One explanation might be that our industrial managers are more familiar with the concept and assessment of probabilities than other subjects such as students or subjects in experiments conducted in developing countries. Explicitly trading off the probabilities and outcomes of various uncertain prospects is a typical component of managerial decision making. For example, the purchasing managers in our sample have to deal with supplier failures on a day-to-day basis. As a result, they are arguably familiar with assigning probabilities to different uncertain events such as delivery failure by suppliers, and so perhaps they are less tempted to subjectively over-weight or under-weight low or high probabilities.

We also tested our results using a power-specification of the probability weighting function, instead of the probability weighting function proposed by Tversky and Kahneman (1992). The estimates for γ did not statistically differ from 1 at standard levels. We therefore conclude that the risk aversion cannot be attributed to probability weighting in an RDU model. We find no structural differences between the results for the RDU model and those for the EUT model.

4.3 PT: The Impact of Sign-Dependent Preferences

Prospect Theory allows for an even richer decomposition of individuals' risk attitudes than EUT or RDU. Our aim here is to determine whether the industrial managers in our sample exhibit (1) sign-dependent preferences leading to different utility functions for gains or losses; and (2) loss aversion, implying that the disutility of losses weighs more heavily than the utility of comparable gains. The four structural parameters estimated here are the reference point χ, α for the curvature of the utility function in the gain and loss domain, γ for the probability weighting function, and λ for the degree of loss aversion.

We first estimate the core parameters for buyers. We determine the reference point using the procedure described earlier. Instead of simply using the reference point induced by the task frame (i.e. the initial endowment of EUR 40), we evaluate different possible reference points ranging from

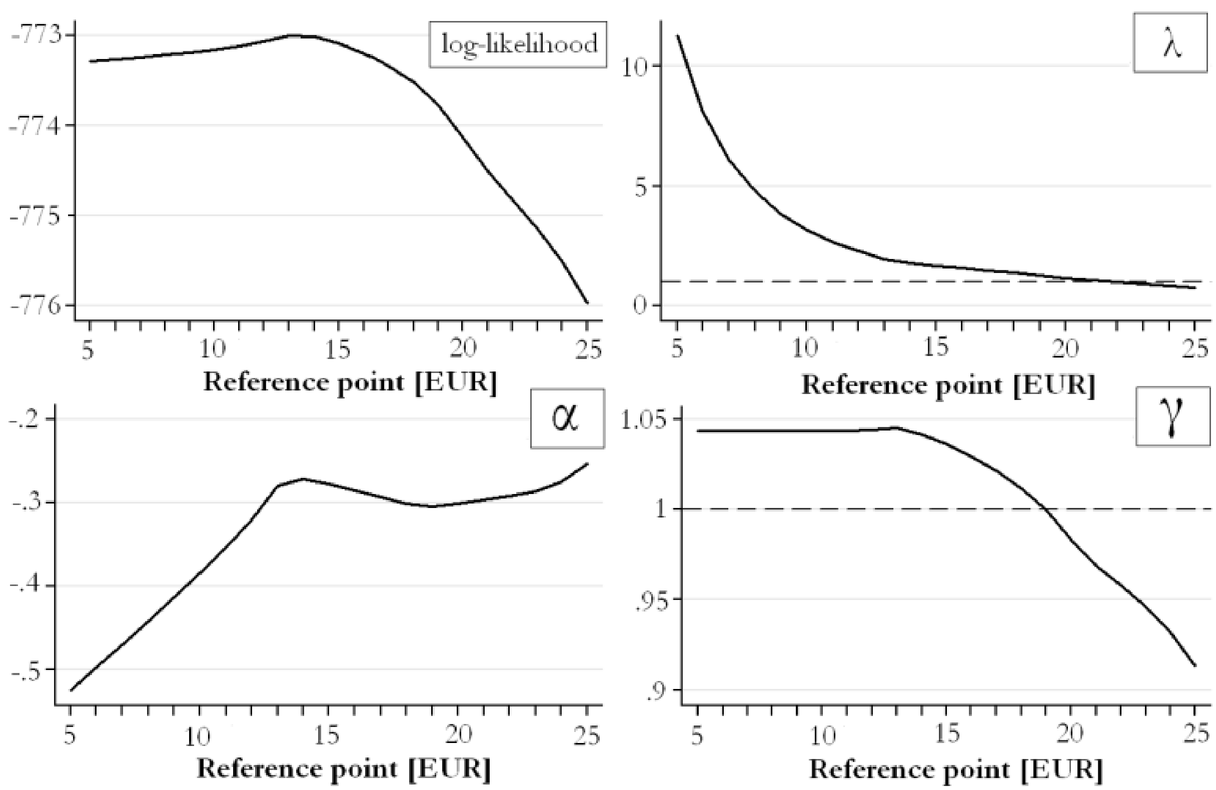

Fig. 3 Tracing the log-likelihood value and parameter estimates for reference points between EUR 5 and 25

EUR 5 to 25 in increments of EUR 1. We trace the maximum log-likelihood value for each of these alternative reference points and use the reference point that yields the highest log-likelihood value for our subsequent analyses. Figure 3 illustrates the results obtained from this procedure. The top left-hand panel traces the log-likelihood value as the reference point is increased, reaching a maximum at EUR 13. Thus the data favors a reference point of EUR 13. This finding suggests that buyers in our sample implicitly assumed that they would earn EUR 13 in the experiment. Consequently, it appears that they interpreted payoffs of more than EUR 13 as gains, and payoffs of less than EUR 13 as losses.

Using this reference point we can decompose the risk attitude of buyers by estimating the probability weighting function, the curvature parameter of the utility function in the gain domain (for outcomes of EUR 13 or more) and the loss domain (for outcomes less than EUR 13), and the loss aversion coefficient. Table 5 gives an overview of the estimates obtained for the PT model.

Table 5 PT model with a CRRA utility specification (assuming α=β)

Subjects	Reference point	Parameter	Estimate	*p*-value	Standard error	Lower 95% confidence interval	Upper 95% confidence interval
Buyers (n=42)	13 EUR	$\alpha = \beta$	-279	28	127	-529	-31
		λ	1960	0	380	1216	2704
		γ	1045	695	115	819	1271
		μ	7692	3	2606	2585	12799
Superiors (n=12)	13 EUR	$\alpha = \beta$	-276	242	236	-739	186
		λ	2876	192	1439	54	5696
		γ	985	953	251	493	1478
		μ	10838	149	7513	55	5697
Non-purchasing managers (n=38)	13 EUR	$\alpha = \beta$	-231	42	114	-454	-8
		λ	2072	0	253	1576	2569
		γ	995	932	62	873	1117
		μ	4876	2	1543	1851	7901

Assuming a reference point of EUR 13, we obtain for α and β a value of -0.28 (*p*-value 0.03) if we assume that $\alpha = \beta$. In contrast to the results obtained from the EUT model, we now observe slight risk-seeking behavior in the gain domain above EUR 13, but risk-averse behavior persists in the loss domain below the reference point. In addition, we find clear evidence of loss aversion. The disutility of losses weighs almost twice as much as the utility of comparable gains: the loss aversion parameter λ is estimated at 1.96 (with a standard error of 0.38). The results indicate that purchasing managers experience a significant disutility from winning less money than they implicitly expected

Comparing these results with our initial estimates, obtained from the EUT specification, leads to some interesting insights. The results from the EUT specification indicated that purchasing managers are risk averse in the global domain of payoffs ranging from EUR 0 to 40. However, the results from the PT model suggest that purchasing managers are only risk averse within the loss domain; in the gain domain, they are moderately risk-loving.

Comparing buyers and their superiors, we find the same reference point of EUR 13 for both groups. However, we cannot draw comparable conclusions for the other model parameters: we cannot reject the hypothesis that α equals 0, and that λ and γ are each equal to 1. This is most likely due to the small sample size: there were only 12 superiors in the sample. Comparing buyers and non-purchasing managers, we find virtually the same results for both groups. For non-purchasing managers, we estimate a reference point of EUR 13, slight risk-seeking behavior in the gain domain (α=-0.23, *p*-value=0.04) above EUR 13, risk-averse behavior below EUR 13, significant loss aversion (λ=2.01, *p*-value=<0.01) and no probability weighting (γ=1.00, *p*-value=0.93 on the null hypothesis that γ=1).

In summary, the reference point is estimated at EUR 13 for all types of managers. All our results indicate slight risk-seeking behavior in the gain domain and risk-averse behavior in the loss domain. The loss aversion coefficient λ ranges from 2.0 to 2.9, depending on the specific type of manager, with superiors exhibiting the greatest degree of loss aversion. A consistent result across all types of managers is the absence of probability weighting. Thus PT provides interesting complementary information to the EUT model, which only characterizes managers as globally risk averse.

It is difficult to compare our findings with those of prior research. The main reason is that we did not use the experimenter-induced reference point of EUR 40 as normally assumed, but determined the reference point that subjects implicitly used when evaluating different lotteries. Our results suggest that subjects had implicit expectations about their earnings, and that they used these expectations to determine which outcomes should be viewed as losses and which as gains.

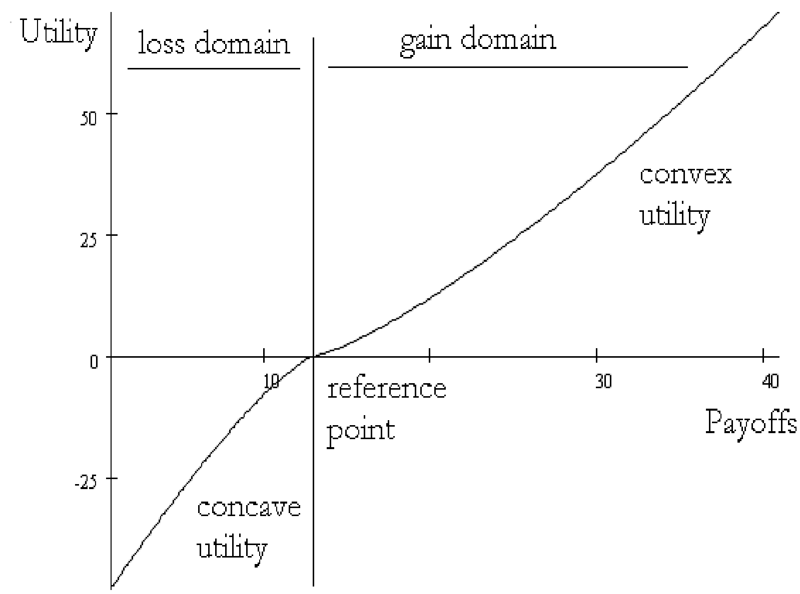

Fig 4. Inverse S-shaped utility function estimated for buyer using a reference point of EUR 13 (α=β=-0.28, λ=1.96)

Using the endogenous reference point of EUR 13, we find an inverse S-shaped utility function as shown in Figure 4 for buyers, convex in the gain domain and concave in the loss domain. This result is not in line with the conventional assumption of most PT analysts who assume an S-shaped utility function implying risk averse behavior in the gain domain and risk seeking behavior in the loss domain. If, however, we simply use the experimenter-induced reference point of EUR 40, we estimate α at 0.19 (*p*-value=0.09) for our group of buyers. This estimate would imply the typical S-shaped utility function. However, the data obtained from our experiments does not support a reference point of EUR 40, despite the loss frame used in our experiment.

The degree of loss aversion may appear to be a confirmation of the argument made by some PT analysts that $\lambda \approx 2$, but it is important to note that λ clearly depends on the assumed reference point, as one can see in Figure 3. Over the range of different reference points that we analyzed, the degree of loss aversion varies between 1 and 10.

In our previous analysis we imposed $\alpha=\beta$, so that the curvature of the utility function was the same in the gain and the loss domain. Köbberling and Wakker (2005) point out that this assumption is needed to identify the degree of loss aversion if one uses CRRA functional forms and does not want to make the strong assumption that utility is measurable only on a ratio scale. Despite this theoretical constraint, we want to assess whether this assumption has an impact on the structural insights gained from our previous results, we now relax this constraint and obtain separate estimates for α and β.

Table 6 PT model with a CRRA utility specification ($\alpha \neq \beta$)

Subjects	Reference point	Parameter	Estimate	*p*-value	Standard error	Lower 95% confidence interval	Upper 95% confidence interval
Buyers (n=42)	13 EUR	α	-279	28	127	-529	-31
		β	-638	0	139	-911	-365
		λ	104	695	115	819	1271
		γ	100	922	62	875	1115
		μ	7692	0	2606	2584	12799

Table 6 gives the corresponding parameter estimates for buyers. For α, we obtain the same estimate as before. However, β now decreases to -0.64. To interpret this decrease, we must simultaneously look at the estimate of λ, as β and λ together determine risk aversion in the loss domain. We find that the additional risk aversion reflected by the increase in β is accompanied by a lower value for λ; the loss aversion parameter decreases from 1.96 to 1.00. Thus our qualitative result is similar to our earlier finding assuming $\alpha=\beta$: risk-loving behavior in the gain domain and risk-averse behavior in the loss domain. We observe the same structural results for superiors and non-purchasing managers.

4.4 Treatment Effects and Biases

We now turn our attention to the treatment effects previously reported for lottery choice experiments. Harrison et. al (2005) and Holt and Laury (2005) provide strong evidence for an order effect. Holt and Laury (2002) show that a hypothetical payment bias is likely to occur if lottery choice experiments do not involve real monetary outcomes. Our experimental design allows us to control for both effects.

Order effects. We controlled for a potential order effect by including a covariate *first*. This covariate captures the potential effect that occurs if the decision task is completed first. It thus indicates whether subjects make different choices at the beginning of the experiment and at the end. We found positive values for the treatment variable, which indicates that the task order had an effect on the risk attitudes of our subjects. However, none of the estimates of the covariate *first* were statistically significant at standard levels. To provide a more extensive test for order effects we conducted a pooled analysis that jointly estimated choices involving real and hypothetical payments, as well as choices across all buyers and superiors. Table 7 provides the estimates obtained from this analysis for an EUT, RDU and PT model.

For the EUT model we find a significant order effect on the CRRA coefficient. The oefficient r is estimated at 0.21 (p-value=0.06) and the order effect captured by the variable *first* is estimated at 0.25 (p-value=0.04). This implies that if we assume that all purchasing managers completed the lottery choice task first, the CRRA coefficient r increases by 0.25 to 0.46. If we assume that they completed the task second or third in order, the estimate of r remains at its initial estimate of 0.21. Thus purchasing managers appear to be more cautious at the beginning of the experiment than at the end. This shows us that the task order does indeed have an impact on the risk attitude of our subjects, although it was not statistically significant in the previous estimations for different groups of subjects.

In the RDU model we also find evidence of an order effect if we conduct a pooled analysis. Interestingly, it appears that whether subjects are risk neutral or risk averse depends on the task order. Looking at tasks completed at a later stage of the experiment, we cannot reject the hypothesis that purchasing managers are risk neutral. The CRRA coefficient is estimated at 0.19, however, with a *p*-value of 0.12. Looking instead at choices made at the beginning of the experiment, we find moderate risk aversion. Despite finding evidence of an order effect on *r*, we do not find any indication of an order effect on γ.

Table 7. Order effect and hypothetical bias

Subjects	Reference point	Parameter	Estimate	*p*-value	Standard error	Lower 95% confidence interval	Upper 95% confidence interval
EUT model and CRRA specification							
Purchasing managers (n=92)	--	r	212	60	113	-9	433
		first	254	38	123	137	495
		hypothetical	-178	131	118	-409	53
		μ	156	0	14	128	184
RDU model and CRRA specification							
Purchasing managers (n=92)	--	r	189	117	121	-47	425
		first	259	40	126	12	506
		hypothetical	-180	135	120	-417	56
		γ	980	705	55	871	1088
		μ	157	0	14	130	185
PT model and CRRA specification							
Purchasing managers (n=92)	13 EUR	$\alpha = \beta$	-306	1	93	-488	-124
		first	94	179	70	-43	231
		hypothetical	-30	675	71	-168	109
		λ	1841	0	312	1230	2453
		first	580	104	357	-120	1280
		hypothetical	-447	170	325	-1084	191
		γ	105	431	72	915	1199
		μ	7601	0	1507	4648	10555

Since we found no evidence of probability weighting, one might expect to see the same estimate for the CRRA coefficient in the EUT and RDU model. However, the introduction of probability weighting prevents a statistically significant estimate for the CRRA coefficient: γ still explains some of the observed choices, although it is indistinguishable from 1 at the 10% level.

In the PT model we also find support for an order effect. The task order does not impact the curvature of the utility function, but it does impact the estimates of the loss-aversion parameter: loss aversion increases from 1.84 to 2.42, and this increase is statistically significant at the 10% level. Thus subjects appear to have experienced a greater disutility from not meeting their expectations in terms of earnings at the beginning of experiment than at the end.

Our findings underline the importance of controlling for task order when subjects complete different decision tasks in the same experiment. However, our qualitative results differ from those of Harrison et al. (2005) and Holt and Laury (2005). While they report that later tasks in an experiment are likely to cause higher relative risk aversion, we find the opposite. In our experiment subjects tended to be more risk averse at the beginning of the experiment than at the end. Although this order effect was not prevalent in our analysis of different sub-samples, we were able to collect evidence of such an order effect by utilizing a pooled analysis. If the order effect had emerged in our analysis earlier (see Tables 3 to 6), we would have needed to adjust the estimates for buyers before comparing their risk attitudes with those of superiors and non-purchasing managers.

Hypothetical bias. The magnitude of a potential hypothetical bias, as reported by Holt and Laury (2002, 2005), is also of interest. We want to assess whether purchasing managers are biased when they face hypothetical economic consequences rather than real payoffs. We capture this potential bias by means of the binary treatment variable *hypothetical*, as shown in Table 7.

Unlike earlier research, we do not find any salient hypothetical bias. In all models (EUT, RDU and PT), the treatment variable *hypothetical* is not statistically significant at the 10% level. This is a surprising finding that might relate to the professional background of our subjects. Since most subjects are purchasing managers with substantial professional experience, it might be that they are accustomed to working with hypothetical scenarios. In the supplier selection process, for example, it is common to work with different (hypothetical) scenarios of potential supplier failures. In addition, van Notten (2006) reports that many companies have even institutionalized the use of tools like scenario planning, which force managers to deal with hypothetical events and force them to evaluate their probabilities and potential consequences. Being more accustomed to the evaluation of hypothetical settings could potentially explain the difference between our results and those reported by Holt and Laury (2002, 2005) for American college students.

4.5 Characteristics Variables

Prior research findings suggest that individual characteristics such as age, sex and education may have an impact on a subject's risk aversion (e.g., Jianakoplos and Bernasek, 1998; Harrison et al., 2007). In the context of industrial managers it is also interesting to explore whether company-specific or job-related characteristics have an effect on the subjects' risk attitudes. For example, we could hypothesize that managers in different industries have varying risk attitudes and that income as well as performance-related salaries impact their decisions under risk. We use the demographic, job-specific and company-specific information that we collected in the first part of the questionnaire to investigate these potential effects. We choose to present the results of our analysis for purchasing managers, since we collected more information from this group of managers than from non-purchasing managers (including details of experience in purchasing, number of suppliers and number of supplier failures in the last 12 months). We also focus on choices involving real payments. The Appendix provides an additional analysis for all managers, albeit with fewer characteristics.

Table 8. Marginal effects of characteristics variables (purchasing managers)

Subjects	Parameter	Description	Estimate	*p*-value	Standard error	Lower/upper 95% confidence interval	
Purchasing	first	Task done first in order	520	78	295	-57	1097
managers	german	Nationality is German	93	735	275	-446	632
(n=54)	female	Gender is female	322	330	331	-326	969
	age_20_35	Age between 20 and 35	507	133	338	-155	1170
	age_36_50	Age between 36 and 50	606	43	300	18	1194
	age_51_65	Age between 51 and 65	330	327	337	-330	991
	married	Marital status is married	288	249	250	-202	778
	household	Household size	-125	858	697	-1491	1242
	business	Business education	-247	153	173	-586	91
	low_income	Household income <45.000 EUR	260	412	318	-362	884
	experience	Total professional experience	1625	8	609	432	2818
	experience_pur	Experience in purchasing	-7	506	10	-28	14
	team_member	No supervisory tasks	55	832	258	-450	560
	bonus	Performance-related salary	-188	343	198	-577	201
	many_suppliers	In charge of >30 suppliers	329	233	276	-212	870
	failure	Supplier failure in last 12 months	-95	753	302	-687	497
	aerospace	Industry is Aerospace	756	2	241	283	1228
	turnover	Turnover of company	-32	913	288	-596	533

Notes: Log-likelihood value is -956.00173. A Wald test for null hypothesis that all coefficients are zero has a χ^2 value of 97.38 with 18 degrees of freedom, implying a *p*-value less than 0.001.

We mainly used binary variables in our analysis. Only the variables *household*, *experience* and *experience_pur* are normalized to lie in the unit interval. Accordingly, we interpret the coefficient on these three variables as reflecting the effect of being e.g. the most experienced subject.

Marginal effects. Apart from the task order, we identify three additional characteristics correlated with variation in risk attitudes across subjects. As shown in Table 8, middle-aged purchasing managers (those aged between 36 and 50) are more risk averse than older or younger purchasing managers. Professional experience also has a statistically significant impact on risk attitude: more experienced managers are more risk averse than less experienced managers. A further interesting finding is that purchasing managers in the aerospace industry tend to be more risk averse than those in other industries. This could be driven by the very restrictive safety regulations and risk precautions that apply in the aerospace industry.

Table 9. Total effects of characteristics variables (purchasing managers)

Subjects	Parameter	Description	Estimate	*p*-value	Standard error	Lower/upper 95% confidence interval	
Purchasing managers (n=54)	first	Task done first in order	296	81	169	-36	628
	german	Nationality is German	129	425	162	-188	446
	female	Gender is female	18	912	168	-310	347
	age_20_35	Age between 20 and 35	-133	424	166	-458	193
	age_36_50	Age between 36 and 50	15	928	162	-302	331
	age_51_65	Age between 51 and 65	177	269	161	-137	493
	married	Marital status is married	227	91	135	-37	491
	household	Household size	275	314	273	-260	810
	business	Business education	-105	497	155	-409	198
	low_income	Household income <45.000 EUR	118	444	154	-184	420
	experience	Total professional experience	470	91	279	-76	1017
	experience_pur	Experience in purchasing	2	847	9	-16	19
	team_member	No supervisory tasks	-158	324	160	-473	156
	bonus	Performance-related salary	-179	237	152	-476	118
	many_suppliers	In charge of >30 suppliers	312	157	220	-120	744
	failure	Supplier failure in last 12 months	-108	500	160	-422	206
	aerospace	Industry is Aerospace	286	99	173	-53	626
	turnover	Turnover of company	68	749	214	-350	487

Notes: Each variable os estimated in a separate model not including other characteristics variables.

Total effects. We now consider the total effects of key characteristics. Total effects may differ from marginal effects. For example, the men in our sample have a number of characteristics that differ from the women apart from their gender. They tend to be older, educated to a higher level, have a higher income and more professional experience. It is possible that the effect of sex along with the characteristics correlated with it have a significant effect on risk attitudes. To determine the total effects, we repeat the analysis in Table 8, but with one characteristics variable at a time. The results are shown in Table 9.

Two of the three significant total effects derive from the same source as the significant marginal effects: professional experience and working in the aerospace industry. In addition, we find a significant total effect of being married. This is probably because most of the married subjects were aged between 36 and 50 (approximately 50% of the married purchasing managers in the sample were aged between 36 and 50).

Our primary reason for collecting a wide range of characteristics variables was that we expected to find significant effects from covariates such as gender, field of education, household income, bonus payments and so on. In fact, we found very few marginal effects and very few total significant effects. One explanation for this could be that industrial managers are a homogenous and self-selected group of subjects. The majority of the subjects in our sample were male (~70%) and had a business or engineering background (~90%). Roughly 60% of the managers had an annual household income of approximately EUR 45,000 and only around 40% received a performance-related salary (i.e., bonus payments).

5. Related Literature

Many studies have measured the risk attitude of students or non-managerial staff. However, we are not aware of any other artefactual field experiments investigating the risk attitude of industrial managers. Here we review selected field and laboratory experiments that relate to our research. In particular, we look at studies with relevance for our key results: the absence of a hypothetical decision bias, the absence of probability weighting, and an inverse S-shaped utility function.

5.1 Similar Studies

Work by Kliger and Levy (2009) is directly relevant to our research. They use real financial market data (call options on the S&P500 index) to assess which model of decision making under risk (EUT, RDU or PT) best characterizes financial investors. They reject EUT in favor of non-linear utility models due to clear evidence of reference point-dependent preferences, non-linear weighting of probabilities and loss aversion. Moreover, their observations are robust to different specifications of the utility function, alternative probability weighting functions and choice of reference point. Comparing the results of Kliger and Levy (2009) with our findings, we identify two main differences. Firstly we cannot reject the EUT specification: We find significant parameter estimates for both EUT and PT. Secondly our estimates, while also robust to different probability weighting functions, are clearly not robust to choice of reference point (see Figure 3).

5.2 Hypothetical Payment Bias

The most widely cited study that deals with hypothetical payment bias is Holt and Laury (2002). In their study they analyze the decision making of 216 undergraduate students. They find that their subjects were, on average, risk averse, and much more so with real payments than with comparable hypothetical payments. Moreover, they found evidence of a scale effect: the degree of risk aversion increases sharply with increases in the scale of real cash payoffs. Under a hypothetical payment treatment, the degree of risk aversion did not change significantly. Even though Harrison et al. (2005) and Holt and Laury (2005) show that the scale effect can partly be attributed to the task order, the hypothetical decision bias persists and is statistically significant.

Our analysis, by contrast, did not reveal a hypothetical decision bias. Managers appeared to be motivated even though they were not personally rewarded for their efforts. One possible explanation for this could be that industrial managers have more experience than, for example, students in dealing with hypothetical scenarios (e.g., from potential supplier failures). Another possibility relates to the experimental setting. The experiments were conducted at the companies' premises and subjects were invited to participate by their superiors. They may therefore have experienced the task as part of their day-to-day business and most carefully evaluated and completed the decision tasks as if they were evaluating hypothetical sourcing scenarios.

5.3 Shape of the Utility Function and Probability Weighting Function

Tversky and Kahneman (1992) propose that the utility function and the probability weighting function exhibit diminishing sensitivity. This leads to an S-shaped utility function, concave for gains and convex for losses, and an inverse S-shaped probability weighting function, implying underweighting of small probabilities and overweighting of large probabilities.

Shape of the utility function. We first focus on the shape of the utility function in the gain and loss domains. Substantial empirical evidence supports the assumption that subjects exhibit a concave utility function in the gain domain (e.g., Tversky and Kahneman, 1992; Abdellaoui, 2000; Abdellaoui et al., 2005). In the loss domain, Tversky and Kahneman (1992), Fenna and Van Assen (1998), Abdellaoui (2000) and Etchart-Vincent (2004) found a slightly convex utility function for losses at the aggregated level. All these researchers estimate the power coefficient of the utility function to be approximately 0.9. If we combine the empirical findings in the gain and loss domains, we obtain the typical S-shaped utility function often assumed by PT analysts.

The inverse S-shaped utility function that we found in our analysis is less common. Nevertheless, Fenna and Van Assen (1998), Abdellaoui (2000) and Etchart-Vincent (2004) report that 20-35% of their subjects exhibit linear and convex utility functions in the gain domain and 30-40% exhibit linear and concave utility functions in the loss domain. Abdellaoui et al. (2008) further report concave utility in the loss domain at the aggregated level.

One possible explanation for why our results differ from the conventional S-shaped utility function might be the endogenous reference point that we used in our analysis. Our approach is consistent with the theoretical framework of Schmidt et al. (2008), who argue that the reference point might be stochastic (e.g., a lottery) rather than deterministic. The contextual nature of the reference point was also pointed out earlier by Kahneman and Tversky (1979). Since the estimated PT coefficients depend on the chosen reference point, it is a simple matter for us to generate an S-shaped utility function. If, for instance, we conduct a pooled analysis and induce a reference point of EUR 40, we obtain a concave utility function in the gain domain and a convex utility function in the loss domain. However, this reference point of EUR 40 is clearly not favored by the data obtained in our experiments.

Probability weighting. Most empirical research on probability weighting points to an inverse S-shaped probability weighting function (e.g., Tversky and Kahneman, 1992; Wu and Gonzalez, 1996; Gonzalez and Wu, 1999; Bleichrodt and Pinto, 2000). Bleichrodt and Pinto (2002), for example, analyzed the decisions made by 51 Spanish undergraduate students. They used a two-step approach: first, they elicited utility functionals, which they then used as input to elicit probability weights. They find strong evidence for probability weighting, concluding that it is a robust result. The common shape of the weighting function is inverse S-shaped, with an inflection point lying between 0.25 and 0.50, consistent with the broad range of similar studies reviewed by Bleichrodt and Pinto (2002). For instance, Tversky and Kahneman (1992), Abdellaoui (2000) and Wu and Gonzalez (1996), who all used the probability weighting function shown in equation (5), estimate γ as lying between 0.6 and 0.7. In our analysis, we did not ignore probability weighting; but at the same time we did not find any evidence in favor of it.

Other researchers who employ a similar methodology to ours also provide evidence of probability weighting. Harrison and Rutström (2009), for example, analyze decisions made by students and allow two competing decision theories under risk, EUT and PT, to explain the choices observed. Estimating a so-called mixture model, they found that their sample was roughly evenly split between those subjects best characterized by EUT and those best characterized by PT. Interestingly, they find no evidence of probability weighting when they estimate a conditional PT model assuming that the whole sample is best characterized by a PT model. The estimated γ parameter is 0.91, but it is not significant at standard levels. When estimating a mixture model, however, γ drops to 0.68 (p-value=0.047) close to the estimates reported by other researchers. This finding may provide further guidance when it comes to interpreting our own results. If most managers in our sample are better characterized by an EUT model than by a PT model, the results of Harrison and Rutström (2009) would explain why we obtain highly significant estimates for the CRRA coefficient assuming an EUT model and no probability weighting when we estimate a PT model assuming that all managers can be characterized by a PT model.

6. Conclusion

We present an artefactual field experiment to characterize risk attitudes' of industrial managers. We recruited 130 managers from 12 industrial companies in Germany, Austria and Switzerland to answer six key questions:

- What risk attitudes do industrial managers exhibit in an artefactual field experiment?
- Do the risk attitudes of managers differ from those of other subjects?
- Do the risk attitudes of superiors differ from the risk attitudes of team members?
- Do the risk attitudes of industrial managers vary across different corporate functions?
- What insights on the risk attitudes of industrial managers can we get from characterizing their behavior using the decision theories EUT, RDU and PT?
- Can the treatment effects identified by researchers investigating other groups of subjects be transferred to industrial managers?

In general, we find that the managers in our sample are moderately risk averse. Assuming a standard EUT model they exhibit similar risk attitudes as other sample populations. However, we find some differences within our sample. Superiors exhibit a higher level of risk aversion than team members that work for them in their department. Comparing purchasing managers with a random sample of non-purchasing managers from different corporate functions such as controlling, sales, engineering and so on, we cannot conclude that they differ from each other.

Comparing different decision theories under risk (EUT, RDU and PT), we show that these theories provide complementary information on the risk attitude of industrial managers. While an EUT model only characterizes managers as globally risk averse, we learn from a PT model that the managers in our sample are only risk averse for a certain range of payoffs. For other payoffs, they even exhibit risk-seeking behavior. The reference point that determines which outcomes are to be viewed as losses and which as gains is not that induced by the task frame. We show that subjects had implicit expectations about their earning in the experiment, and used these expectations to evaluate the lotteries presented to them.

We find that managers differ from other subjects, and that methodological insights gained from student subjects cannot be readily transferred to industrial managers. The managers in our sample did not weigh probabilities and they did not exhibit a hypothetical decision bias. One potential explanation for this difference might be that managers are more familiar with the concept and assessment of probabilities than other subjects as management concepts. Managers are also used to work with hypothetical scenarios, which might explain the absence of a hypothetical decision bias.

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Appendix: Additional Results

Table A1. Marginal effects of characteristics variables (all managers)

Subjects	Parameter	Description	Estimate	*p*-value	Standard error	Lower/upper 95% confidence interval	
Decisions of all managers over own money with real payments (basic design)							
All managers (n=92)	first	Task done first in order	210	161	150	-84	504
	german	Nationality is German	189	167	137	-79	457
	female	Gender is female	319	12	128	69	567
	age_20_35	Age between 20 and 35	367	88	215	-54	787
	age_36_50	Age between 36 and 50	321	82	185	-41	684
	age_51_65	Age between 51 and 65	502	26	225	60	943
	married	Marital status is married	87	578	157	-220	395
	household	Household size	-29	909	250	-518	461
	business	Business education	-122	281	113	-342	100
	low_income	Household income <45.000 EUR	181	165	130	-74	436
	experience	Total professional experience	307	447	404	-485	1100
	team_member	No supervisory tasks	-140	349	149	-432	153
	bonus	Performance-related salary	-65	625	132	-324	195
	aerospace	Industry is Aerospace	91	493	134	-171	354

Notes: Log-likelihood value is -1604.9237. A Wald test for null hypothesis that all coefficients are zero has a χ^2 value of 20.90 with 14 degrees of freedom, implying a *p*-value of 0.10.

Table A2. Total effects of characteristics variables (all managers)

Subjects	Parameter	Description	Estimate	*p*-value	Standard error	Lower/upper 95% confidence interval	
Decisions of all managers over own money with real payments (basic design)							
All managers (n=92)	first	Task done first in order	194	124	126	-53	441
	german	Nationality is German	102	358	111	-115	319
	female	Gender is female	107	317	107	-106	316
	age_20_35	Age between 20 and 35	-46	642	99	-241	148
	age_36_50	Age between 36 and 50	-13	904	103	-215	190
	age_51_65	Age between 51 and 65	137	244	117	-93	367
	married	Marital status is married	100	298	96	-88	287
	household	Household size	68	696	174	-274	410
	business	Business education	-113	246	98	-305	78
	low_income	Household income <45.000 EUR	87	408	105	-119	293
	experience	Total professional experience	166	427	209	-243	574
	team_member	No supervisory tasks	-112	279	103	-313	90
	bonus	Performance-related salary	-97	358	106	-304	110
	aerospace	Industry is Aerospace	92	403	110	-124	308

Notes: Each variable os estimated in a separate model not including other characteristics variables.