Managers' Risk Preferences and Firm Training Investments*

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Abstract

We provide the first estimates of the impact of managers' risk preferences on their training allocation decisions. Our conceptual framework links managers' risk preferences to firms' training decisions through the bonuses they expect to receive. Risk-averse managers are expected to select workers with low turnover risk and invest in specific rather than general training. Empirical evidence supporting these predictions is provided using a novel vignette study embedded in a nationally representative survey of firm managers. Risk-tolerant and risk-averse decision makers have significantly different training preferences. Risk aversion results in increased sensitivity to turnover risk. Managers who are risk-averse offer significantly less general training and, in some cases, are more reluctant to train workers with a history of job mobility. All managers, irrespective of their risk preferences, are sensitive to the investment risk associated with training, avoiding training that is more costly or targets those with less occupational expertise or nearing retirement. This suggests the risks of training are primarily due to the risk that trained workers will leave the firm (turnover risk) rather than the risk that the benefits of training do not outweigh the costs (investment risk).

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1 Introduction

Management practices are instrumental to organizational performance. Practices that support the efficient acquisition, sharing, and utilization of knowledge seem to drive innovation (Inkinen, 2016). Productivity is higher in firms with innovative work practices (e.g. performance pay, problem-solving teams, training, etc., see Ichniowski *et al.*, 1997; Ichniowski and Shaw, 1999) and management structures that support performance monitoring, incentives, and targets (Bloom and Van Reenen, 2007; Bloom *et al.*, 2013, 2019).[1] Importantly, individual managers can shape organizational outcomes. Bertrand and Schoar (2003), for example, find that manager fixed effects are linked to firm performance as well as to financial and investment decisions. They conclude that managerial decision-making can be characterized by specific patterns consistent with the existence of heterogeneity in managerial "style". In related research, Bandiera *et al.* (2020) differentiate CEOs by how they spend their time; some are "managers", primarily involved with production-related activities, while others are "leaders", primarily involved in communication and coordination activities. Neither managerial approach is best practice across all firms, however, and the authors provide evidence that many CEO-firm pairs are misassigned leading to productivity losses.

We know less about the mechanisms through which managers influence organizational outcomes. The literature has generally "modelled the relationship between boss and worker at an abstract level and has not pushed beyond to examine what is likely to be the most important relationship in the workplace" (Lazear *et al.*, 2015, p. 824). Making progress requires that we move beyond black-box estimates of managers' overall impact to develop a deeper understanding of the individual traits, skills, and practices that matter. Along these lines, Hoffman and Tadelis (2021) have recently demonstrated that survey-based measures of managers' people management skills are negatively related to employee turnover. Linking specific manager characteristics to organizational performance is challenging using observational data, because managers are not randomly allocated to firms or indeed to jobs within firms (Bertrand and Schoar, 2003; Hoffman and Tadelis, 2021) and detailed information about their prior work experience is often lacking (Hall and Pedace, 2016).

We address this issue by conducting a vignette study of the way that managers' attitudes towards risk influence their allocation of employment-related training opportunities. This focus on risk and risk preferences is an important contribution of our research. Strategic management

[1] These management effects are economically large. Bloom *et al.* (2019), for example, estimate that management practices account for 20 percent of the variation in productivity across U.S. manufacturing plants; a fraction that is similar to, or greater than, that attached to R&D, ICT or human capital. Schivardi and Schmitz (2020) argue that a large part of the lower productivity growth in Southern Europe is caused by inefficient management practices that limited potential gains from the IT revolution since the middle of the 1990s.

is, after all, fundamentally about decision making under uncertainty, making managers' risk tolerance crucial for the decisions they make.[2] Despite this, the consequences of managers' risk preferences have not been extensively studied. In a recent review of the empirical personality-based management literature, for example, Abatecola *et al.* (2013) find that risk attitudes feature in only 11 percent of the studies they review.

The context in which our study is grounded – employment-related training investments – extends the contribution we make. Training decisions, like other investment decisions, are risky with estimates of the average return varying from seven to 50 percent (Bartel, 2000).[3] They are also consequential. Enhancing workers' skills improves firms' competitiveness by raising firm-level productivity (Barrett and O'Connell, 2001) and continuous employee development is widely regarded as key to organizational survival (e.g. Tannenbaum, 1997; Garavan, 2007).[4] As managers are typically the primary gateway to employees' development opportunities (McDowall and Saunders, 2010), the risks associated with workplace training are particularly salient for the decision makers we study. Studying training investments from their perspective is an important addition to the literature given the strategic imperative of national governments and international development agencies to raise investment in work-related education and training (see OECD, 1996; European Commission, 2007).[5]

We begin by developing a stylized model linking managers' risk preferences to the profitability of firms' training investments. Managers' training decisions are modeled as inter-temporal choices made under uncertainty. Risk-neutral firms are assumed to incentivize risk-averse managers to make profitable training decisions by paying bonuses. Managers maximize their expected utility, which is increasing in income and dependent on their degree of risk aversion. Thus, our model implies that the chances a worker is offered training is positively related to his manager's tolerance for risk.

We consider two underlying sources of risk in our model. While the costs of training are known, managers are uncertain about the profitability of training because: i) there is a risk that training will not be productive; and ii) there is a risk that trained workers quit before the

[2] March and Shapira (1987) discuss the conceptual way that managers think about risk. See Hoskisson *et al.* (2017) for a recent review of the management literature on agency theory and managerial risk taking.

[3] In their meta-analysis of the role of training in organizational outcomes, Tharenou *et al.* (2007) conclude that training is positively related to human resource outcomes and organizational performance but is only very weakly related to financial outcomes.

[4] Evidence of the causal effect of training on firm outcomes is somewhat limited. Grip and Sauermann (2012) provide evidence from a field experiment that training generate positive externalities by raising the productivity of the untrained co-workers of training participants. Using a difference-in-difference strategy, Martins (2021) shows that training grants provided to firms through a competitive process led to enhanced performance on a number of dimensions.

[5] For reviews of the work-related education and training literature see Bishop (1996); Blundell *et al.* (1999); Asplund (2005); Leuven (2005); Bassanini *et al.* (2007); Frazis and Loewenstein (2007); Wolter (2011); Haelermans and Borghans (2012).

firm recoups its training investment. Managers with a low tolerance for risk are expected to be particularly focused on directing training opportunities to those workers for whom training has a relatively low risk of being unproductive. Moreover, turnover risk is higher for general training that is transferable to outside opportunities than for specific training that is not (Becker, 1962; Bishop, 1996; Acemoglu and Pischke, 1999b). Risk-averse managers are therefore expected to be especially reluctant to offer general training to workers. Turnover risk will also be higher for some workers than for others. For this reason, risk-averse managers may be less likely to offer training to workers with a history of job mobility or who are statistically more likely to quit. Finally, we expect risk-averse managers to be more sensitive to both the direct and opportunity costs of training because high training costs increase the chances that the training will not be profitable for the firm.

We then test these predictions using a novel vignette study in which targeted vignettes were incorporated into a nationally representative survey of German firms.[6] These vignettes involve fictitious training scenarios that were presented to survey respondents – primarily firm owners and human resource managers typically making such decisions on a daily basis – who were then asked which of two workers they would choose to train.[7] Randomization of i) the length of training; ii) the share of training costs paid by the firm; and iii) the transferability of training provides us with exogenous variation in the chances that training will be profitable, and hence, in the risk that managers face. Additional random variation in the fictitious CVs of the workers to be trained contributes to our identification strategy by forcing managers – who vary in their own attitudes towards risk – to trade off the expected returns associated with workers' gender, age, occupational expertise, and previous job mobility with the risks stemming from the cost and transferability of training.

Our results provide the first estimates of the impact of managers' risk preferences on their employment-related training decisions. We show that managers are more willing to provide training to both young and workers with more occupational expertise. While gender does not play a major role, workers with a history of job mobility have less chance of being offered training. Most importantly, managers strongly prefer training that is usable only in their firm. This is especially true for risk-averse managers. They are about 30 percent less likely to send a worker to training that is completely transferable to other firms. Our findings advance the behavioral economics and management literature by documenting the importance of managers'

[6]Vignette methods have been used to study a variety of labor market issues including gender discrimination in hiring (Kübler *et al.*, 2018), individuals' willingness-to-pay for fringe benefits and job amenities (Eriksson and Kristensen, 2014), and managers' decisions regarding telework (Beham *et al.*, 2015), worker retention (Buers *et al.*, 2018) and recruitment (Karpinska *et al.*, 2011; Humburg and van der Velden, 2014; Mulders *et al.*, 2014).

[7]Karpinska *et al.* (2015), Fleischmann and Koster (2017), and Poulissen *et al.* (2021) use a similar vignette design to study the factors driving Dutch firms' decisions to train older and temporary workers.

risk attitudes for firm-level decision making. As such, our vignette study complements previous observational studies examining the implications of management style, strategy, and practice for organizational outcomes.

2 Theoretical Framework

We present a stylized model of a firm's decision to invest in training. Firms are assumed to be risk-neutral and profit maximizing. Each firm employs a manager i who decides at the beginning of a period whether or not to invest in training worker j. Workers take up training if managers offer it. Managers are risk-averse, and the degree of risk aversion θ_i varies across managers. The costs c of training H are known to the manager, while the returns from training are uncertain. With probability p the training is successful and leads to an increase in the revenue of the firm (O) which exceeds training costs (c). The firm observes both the cost of the training investment and the subsequent gain in revenue, if training occurs.

Managers' base wage in the absence of any training investments is w_0. Firms incentivize managers to make profitable training decisions by paying bonuses and imposing penalties. If the manager makes a training investment that is successful, the firm's profits will increase and the firm responds by paying a bonus payment B to manager i. If the training investment is not productive, there is a decrease in firm profits resulting in manager i incurring a wage penalty of D. The utility (U) of manager i depends positively on her take-home wage (including bonuses and penalties) and the shape of this relationship depends on θ_i. The expected wage of the manager if the worker is trained is $E(w|H_j = 1) = w_0 + pB - (1-p)D$. The manager's expected values of training worker j ($H_j = 1$) and not training worker j ($H_j = 0$) conditional on risk aversion θ_i are given by:

$$\begin{aligned} V_i(H_j = 1|\theta_i) &= pU(w_0 + B|\theta_i) + (1-p)U(w_0 - D|\theta_i), \qquad (1) \\ V_i(H_j = 0|\theta_i) &= U(w_0|\theta_i). \qquad (2) \end{aligned}$$

Manager i offers a training to worker j if

$$pU(w_0 + B|\theta_i) + (1-p)U(w_0 - D|\theta_i) > U(w_0|\theta_i).$$

Whether or not a manager offers training to a worker depends on i) the probability that this training leads to an increased profit; ii) the utility gain associated with the corresponding increase in the manager's income; and iii) the potential utility loss if training is not profitable and there is a corresponding decrease in the manager's income. The expected utility gain of training worker j will be larger for a risk-tolerant manager than for a manager who is more risk-averse. This implies that the probability of offering training to a worker negatively depends on the risk aversion of the manager.

The literature points to two main sources of risk in firms' training decisions. First, there is a risk that training is not useful and leaves worker productivity unchanged. This returns risk primarily stems from uncertainty about: (i) how quickly training investments become obsolete; (ii) unobserved heterogeneity in workers' ability to benefit from training; (iii) firm-specific competitiveness and profitability; and (iv) the overall quality of the training (see e.g. Levhari and Weiss, 1974; Williams, 1979; Shaw, 1996). Second, risk is generated by worker turnover, i.e. the possibility that trained workers leave the firm before it has had time to recoup its training investment. Firms can reduce this risk by targeting training towards workers with a lower propensity for turnover, using contracts that impose penalties for premature quitting (see Hoffman and Burks, 2017), and establishing employment practices that encourage long-term relationships and worker reciprocity (see Frazis *et al.*, 2000; Leuven, 2005; Sauermann, 2021).[8] Crucially, the investment risks created by worker turnover vary not only with worker characteristics (e.g. skill levels, propensity to quit, etc.), but also with the nature of training itself. Workers are more likely to leave the firm if the training they receive is general and easily transferred to other employers than when it is specific to their current employer.[9] For this reason, managers face more turnover risk when making general training investments than when making specific training investments, everything else equal.[10]

In our vignette study, we randomly vary the characteristics – and consequently the risks – of the training on offer. First, we vary the length of the training, i.e., the intensive margin of the training investment. Second, we randomly vary the share of the direct training costs paid by the employer. Third, we also randomly vary the type of training, i.e., the degree to which the workers can use the skills developed in other firms. This allows us to test empirically whether

[8]Frazis and Loewenstein (2007) discuss all of these issues in their comprehensive review of the on-the-job training literature.

[9]Dietz and Zwick (2020), for example, show that, overall, the retention effect of training is positive; trained employees are more likely to remain at the firm than are employess who randomly miss out on training. At the same time, this retention effect is smaller for training that is portable and verifiable.

[10]Becker (1962) was the first to highlight the fundamental role that skill transferability has in the allocation of training costs. He argued that, in perfectly competitive markets, worker turnover eliminates a firm's ability to profit from any general training that it provides. Instead, firms have an incentive to pay only for specific training, while workers' have an incentive to pay for their own general, but not specific, training. This insight has given rise to numerous studies investigating the circumstances in which firms' provide general training. The consensus from this large literature is that employer-provided general training may continue to be profitable – despite worker turnover – if there are labor market rigidities, non-competitive market structures, information asymmetries, or training is both general and specific (see Acemoglu and Pischke, 1999a; Asplund, 2005; Leuven, 2005; Frazis and Loewenstein, 2007, for reviews). Nonetheless, worker turnover dampens the profitability of firms' training investments. At the same time, this may be mitigated to the extent that general training involves less investment risk because it is more likely to raise worker productivity (see Barrett and O'Connell, 2001; Asplund, 2005; Dearden *et al.*, 2006).

more risk-averse managers are less likely to invest in training that i) is longer; ii) involves higher costs; and iii) is more easily transferable to other firms. Finally, we also randomize some key worker characteristics (age, gender, qualifications, previous job mobility) which potentially affect training decisions in ways that depend on managers' risk preferences.

3 Study Design, Data, and Descriptives

Our vignette experiment is embedded in the Cost-Benefit Survey 2018 of the Federal Institute for Vocational Education and Training (BIBB). This survey aims to elicit the costs and benefits of vocational training and recruitment within German firms (see Schönfeld *et al.*, 2020). Responding firms are randomly drawn from an administrative register, housed at the Federal Employment Agency (*Bundesagentur für Arbeit*), of all firms with at least one employee subject to social security contributions. Thus, our sample is representative of the universe of all German firms. Survey respondents are firm owners and human resource managers who are regularly involved in actual training decisions.[11] They first answer several batteries of questions focused on the vocational training of employees before undertaking the vignette experiment. Finally, in the last part of the survey the respondents provide information about themselves (e.g. personality traits, risk preferences, experience, etc.).[12] In the experiment, respondents are presented with six choice scenarios involving employees requesting permission to undergo training. These hypothetical scenarios correspond well with the types of decisions they typically make on a daily basis.

In total, around 4,000 firms participated in the 2018 BIBB Cost-Benefit Survey. Of these, approximately one third (1,358) were randomly selected to take part in the vignette experiment. After excluding respondents who were not willing to participate and those from firms with multiple representatives participating in the survey, we are left with a sample of 1,161 firm representatives ($\approx$ 85 percent).

3.1 Vignette Design

In the vignette experiment, respondents are repeatedly confronted with two hypothetical training candidates in different training scenarios. Each of the two candidates is characterized by four attributes: gender, age, occupational expertise, and previous job mobility. Each of the

[11] Aligning the sample and the target population by surveying and selecting those firm representatives that have decision-making power is an important step in ensuring the external validity of our discrete choice experiment (see Hainmueller *et al.*, 2015, for details).

[12] The interviews take place in the firm using the computer-assisted personal interviewing (CAPI) method. To reduce the risk of a social desirability bias in the face-to-face interviews, the interviewer hands over the laptop to the respondent when answering the vignette and when revealing personal information.

two corresponding training scenarios is characterized by three attributes including the transferability and duration of training as well as the cost sharing agreement between the employer and the employee. An overview of all attributes and attribute values is provided in Table A.1, while Figure 1 provides an example of the choice set-up as seen by the respondents during the interview. Each respondent is presented with six choice sets consisting of two alternatives. Each of the two alternatives represents a hypothetical training candidate and training scenario that is fully characterized by a total of seven attributes with values that are randomly generated from a predefined set.[13]

[Insert Figure 1 here]

We create efficient choice designs using a two-step approach. First, we reduce the number of alternatives to 216 (108 choice sets). Second, we group the 108 choice sets into 18 blocks resulting in six choice sets (each with two alternatives) per block. Each respondent is asked to complete one block of six choice sets. The distribution of the 18 blocks among respondents is randomized as is the order of choice sets within any block.[14] The total number of possible choice sets in a full factorial design exceeds 1.8 million.[15] Including all of them in our study would be neither time- nor cost-effective. Instead, we reduce the number of choice sets and employ a fractional factorial design that meets the requirements for an efficient choice design proposed by Huber and Zwerina (1996).[16] The frequency of attribute values is equalized across the two choices (see column (1) in Table 1) in line with the level balance requirement. Moreover, consistent with the minimal overlap property, it is the case that, in every choice set, attribute values always differ across the two choices, forcing respondents to make a choice between different attribute values. The actual choices made by decision makers are summarized in Column (2) of Table 1. They highlight that women, younger candidates and those with above average occupational expertise are chosen for training more frequently. The training context also matters with specific training (only usable in the firm) and shorter training (taking 2 working days) being chosen more frequently.

[Insert Table 1 here]

[13] The total number of possible vignettes therefore amounts to 1,944 (2 x 4 x 3 x 3 x 3 x 3 x 3).

[14] In doing this, we make use of the user-written Stata module *dcreate* (Hole, 2015).

[15] Specifically, there are 1,944 distinct vignettes which can be combined into (1944x1943)/2 = 1,888,596 choice sets.

[16] Huber and Zwerina (1996) propose four properties for efficient choice designs: (1) orthogonality, (2) level balance, (3) minimal overlap, and (4) utility balance.

3.2 Estimation Sample

We make two sample restrictions. Some vignette participants (n = 117) do not make all of the training decisions presented to them and they are dropped from the sample. In addition, we restrict our sample to participants who answer the question on risk tolerance. These restrictions result in a final estimation sample of 6,339 training decisions involving 12,678 choice alternatives which we use to assess the link between decision makers' risk preferences and their training choices.

[Insert Table 2 here]

Our vignette participants are predominantly men (57 percent, see Table 2). Most are highly educated; 44 percent have an academic degree, while 35 percent have an advanced vocational degree and a further 20 percent have a vocational degree. Importantly, respondents are decision makers who hold a range of senior positions within their firms including: firm owners (35 percent), CEOs (13 percent), department heads (7 percent), and heads of human resources (18 percent), commerce (8 percent), and training (7 percent). On average, they have approximately 14.5 years of firm tenure. A small proportion (11 percent) of the firms they work for are export-oriented, while the majority of participants (67 percent) report that their firms are in highly competitive markets.

One key advantage of our data is that they provide information about managers' personality traits and economic preferences. Previous vignette studies of worker training have either focused solely on the attributes of training scenarios themselves (see Fleischmann and Koster, 2017; Poulissen *et al.*, 2021) or accounted only for managers' age, education, and organizational position (Karpinska *et al.*, 2015). Our data include among other things, measures of locus of control, Big-5 personality traits, patience, and, most importantly for our analysis, attitudes towards risk. Risk preferences are captured through responses to the following question: "How do you see yourself: Are you generally a person who is prepared to take risks or do you try to avoid taking risks?". Respondents answer using an 11-point Likert scale that ranges from "not at all willing to take risks" to "very willing to take risks". The behaviorial validity of this measure has been confirmed using incentivized experiments (Dohmen *et al.*, 2011).

The distribution of risk tolerance in our sample of decision makers is shown in Figure A.1A in the Appendix. The mean risk preference is 5.46 (median = 6) in our sample, which is higher than in that for a representative sample of the German population captured in the 2018 German Socio-Economic Panel (SOEP) (see Figure A.1B). The risk tolerance of our vignette participants is, in fact, more similar to SOEP respondents in high-status occupations (see

Figure A.1C). This finding is in line with Dohmen *et al.* (2011) who find that those working in high-status occupations are more tolerant towards risk than the population on average. In our empirical analysis, we consider a continuous measure of decision makers' risk preferences as well as a binary indicator that differentiates relatively risk-averse (i.e. > median) from risk-tolerant (<= median) decision makers. Approximately, 64.1 percent (4,065 out of 6,339) of the total training choices are made by risk-averse decision makers, whereas 35.9 percent (2,274 out of 6,339) of the decisions are made by relatively risk-tolerant decision makers.

4 Empirical Strategy

4.1 Estimation Approach

Each participant i in our vignette study – referred to as a decision maker – makes repeated choices between two alternative candidates k and s.[17] We assume that participants maximize their utility. Thus, given choice set t, decision maker i chooses alternative k if

$$U_{ikt} > U_{ist}, \ \ \forall s \neq k.$$

Each choice alternative j in choice set t of our experiment can be completely characterized by the observed attributes x_{ijt} of the hypothetical training candidate and training context as described in the vignette. Decision maker utility is specified as a linear function of the observed choice alternative attributes x_{ijt}:

$$U_{ijt} = \beta_i' x_{ijt} + \epsilon_{ijt}, \tag{3}$$

where β_i is an individual-specific coefficient vector capturing heterogeneity in preferences for various training options and ϵ_{ijt} is an unobserved random error term that is assumed to be independent and identically distributed. The coefficient vector can be decomposed as $\beta_i = \bar{\beta} + \nu_i$ where $\bar{\beta}$ denotes the population mean and ν_i captures unobserved individual-specific deviations from the population average.

Our specification has the advantage of allowing decision makers to have different (unobserved) preferences over the attributes of choice alternatives. Unobserved heterogeneity is accounted for through ν_i. We assume that ν_i is uncorrelated with the observed attributes of choice alternatives x_{ijt} and model it as a random effect. This maintained independence assumption is

[17] In our theoretical framework, a decision maker chooses to train or not to train a worker. A worker gets a training if the (expected) utility of the decision maker is positive. The underlying parameters describing the (relative) utility can be estimated either based on a sample with agents choosing one among several alternatives - as in our vignette study - or in a set-up in which agents make a binary choice facing one option which they choose or not choose (Train, 2009).

usually quite strong in non-experimental studies. In our research design, however, we randomly allocate choice alternatives to the choice sets of the decision makers. Given this, there is no reason to expect a correlation between the unobserved preferences of decision makers and the observed attributes of the choice alternatives.

We derive the choice probabilities for different training alternatives by assuming that the random error terms ϵ_{ijt} follow an extreme value distribution. This results in a mixed logit model. The individual likelihood contribution L_i conditional on unobserved heterogeneity is described by:

$$L_i|\nu_i = \prod_{t=1}^{T} \frac{\exp(\beta_i' x_{i1t})^{d_{i1t}} \exp(\beta_i' x_{i2t})^{1-d_{i1t}}}{\sum_{j=1}^{2} \exp(\beta_i' x_{ijt})}.$$

where d_{i1t} is a dummy variables which is equal to one if individual i chooses alternative $j = 1$ in choice set t. The coefficients β_i are distributed with density $f(\beta|\theta)$, while θ is a vector containing the parameters of this distribution. The unconditional likelihood is given by the integral over this distribution:

$$L_i = \int \prod_{t=1}^{T} \frac{\exp(\beta_i' x_{i1t})^{d_{i1t}} \exp(\beta_i' x_{i2t})^{1-d_{i1t}}}{\sum_{j=1}^{2} \exp(\beta_i' x_{ijt})} f(\beta) d\beta.$$

The log likelihood for a sample with n observations is given by:

$$\ln L = \sum_{i=1}^{n} \ln \left(\int \prod_{t=1}^{T} \frac{\exp(\beta_i' x_{i1t})^{d_{i1t}} \exp(\beta_i' x_{i2t})^{1-d_{i1t}}}{\sum_{j=1}^{2} \exp(\beta_i' x_{ijt})} f(\beta) d\beta \right). \tag{4}$$

We estimate the parameters of the continuous mixing distribution using maximum simulated likelihood (see Revelt and Train, 1998; Train, 2009). In the approximation of the integrals we employ Halton draws to reduce the simulation variance (see Train, 1999; Bhat, 2001; Haan and Uhlendorff, 2006). Since standard Halton sequences tend to be highly correlated for higher-dimensional integrals, we also scramble the Halton sequence using the standard square-root scrambling method proposed by Kolenikov (2012).[18]

4.2 Model Selection

We consider model selection by estimating a series of models with alternative approaches to account for i) unobserved heterogeneity; and ii) training costs. Our results are presented in Table 3.

We begin by comparing standard (conditional) logit estimates that do not account for unobserved heterogeneity (column 1) with mixed logit estimates that do. Specifically, we estimate

[18] We estimate the mixed logit models with Stata using the routines by Hole (2007).

two alternative mixed logit models. The first is a restricted specification with uncorrelated random coefficients (column 2). The second specification allows for an unrestricted variance-covariance matrix for the random parameters (column 3). In both mixed logit models, we assume that the unobserved heterogeneity follows a multivariate normal distribution.

[Insert Table 3 about here]

The estimated mean coefficients in the two mixed logit models tend to be larger than the coefficients estimated using the standard logit model (column 1). Moreover, estimated mean coefficients tend to be larger when we allow for correlation in the random effects (column 3) than when we estimate the restricted mixed logit model (column 2). These patterns reflect the fact that the variance in the error term ϵ_{ijt} is smaller the more flexibly we specify the distribution of the random effects. The (correlated) random effects explain a large part of the variance in the choice patterns (for similar results see, for example, Revelt and Train, 1998; Eriksson and Kristensen, 2014). In the mixed logit model without correlation in the random coefficients, half of the estimated standard deviations of the coefficients are significant, while in the mixed logit model allowing for correlated random effects, all estimated standard deviations are significant. Moreover, the log-likelihood decreases substantially as we move from a standard logit model to the restricted mixed model and then to the unrestricted mixed logit model. Taken together, these results provide evidence that the preferences of decisions makers vary and that a mixed logit model is more appropriate than a standard logit model when analyzing our data. The Akaike Information Criterion indicates that the mixed logit model allowing for correlation in the random effects is the preferred model specification, while the Bayesian Information Criterion indicates that the mixed logit model without correlated random effects is the preferred specification. At the same time, there is a stable pattern in the sign and significance of the (mean) coefficients across specifications. The same is true if we consider the ratios of coefficients. For example, the ratio of the estimated coefficients for prior job mobility and training duration changes only slightly, from 9.2 to 10.1 when we move from the standard logit model to the flexible mixed logit model even though the absolute size of both coefficients almost doubles. Given the stability of the results for the (mean) coefficients across the three model specifications, in the following, we will mainly present and discuss results based on the mixed model with uncorrelated random parameters.

We next consider the way that we account for training costs. In our vignette experiment, the direct costs for the training do not vary and are fixed at €250 per day. Using this information along with the cost sharing rule (0%, 50%, or 100%) and the duration of the training (2, 5, or 10 days), decision makers can calculate the overall direct training costs faced by the employer in each choice alternative. We report the results for specifications that incorporate direct training costs rather than the cost sharing rule in columns (4) and (5) of Table 3. As expected, the results in column (4) show that the direct costs of training have a significantly negative effect on the probability of decision makers choosing the corresponding training alternative. Relative to our restricted mixed logit model in column (2), the (mean) coefficient for training duration decreases, but remains negative and significant at 1 percent. Estimates for the other attributes of the choice alternative are also very similar to those reported in column (2). Finally, the assumption that unobserved heterogeneity in our mixed logit models follows a multivariate normal distribution implies that we do not restrict the attributes of choice alternatives to have either a positive or a negative effect on decision maker utility. While this seems plausible for most of the training choice attributes we consider, economic theory clearly predicts that training costs will result in disutility for decision makers. Consequently, we also specify a log-normal distribution for the parameter of the direct costs in column (5). As the log-normal distribution is defined from zero to infinity, this specification ensures that the sign of the effect of (negative) costs will be positive for all decision makers. We report the exponential of the estimated mean of this coefficient to make it comparable with the normally distributed coefficients. Estimates for the cost parameters, as well as for the other attributes of the choice alternative, are very similar to those in the specification with normally distributed cost parameters. In line with this, the log-likelihood values in the two models are also very similar suggesting that they fit the data equally well. Consequently, in Section 5, we will mainly focus our discussion on results from the specification with normally distributed cost parameters.

5 Results

5.1 Training Offers

Our objective is to understand how decision makers' training offers vary with the attributes of the proposed training candidate and training context. The logit results presented in Table 3 are informative about the direction and statistical significance of estimated effects. However, they are difficult to interpret and provide little insight into the economic importance of different choice attributes for the chances that training is offered. Consequently, we present estimated marginal effects in Table 4.[19]

[Insert Table 4 about here]

[19] The calculation of the marginal effects is based on the 6,339 choice sets in our vignette study.

Decision makers are slightly more likely (1 percentage point) to offer training to female candidates than to their male counterparts. The absence of a gender gap in training offers is striking given that managers' evaluations of applications for apprenticeships appear to be gender-biased. Specifically, in related research, Kübler *et al.* (2018) also rely on a vignette-based factorial survey embedded in a BIBB survey; they find that female job candidates for apprenticeship positions face an evaluation penalty equivalent to having a grade point average that is one grade lower. Together, these results suggest that any gender discrimination in training opportunities takes place in entry into training positions not in training offers for established workers.

In contrast, training opportunities are directed towards candidates who are more skilled. Having average rather than low occupational expertise increases the chances of being offered training by nearly 9 percentage points; candidates with above average occupational expertise are 13 percentage points more likely to be offered training. Differential training offers may therefore provide a potential explanation for the higher incidence of work-related training among workers with higher ability (as measured by aptitude scores) and more formal education (e.g. Arulampalam and Booth, 1997; Asplund, 2005; Bassanini *et al.*, 2007). Decision makers also clearly prefer to train younger workers. A 25 year-old worker, for example, has a probability of being offered training that is 13 percentage points higher than that of a 55 year-old worker. This age penalty is nearly the same as that between 45 and 55 year-olds (11 percentage points) suggesting that, rather than strictly favoring young workers, decision makers wish to avoid training workers nearing retirement. A vignette study of Dutch managers' training decisions also finds evidence of an age penalty in training offers within a group of older workers (aged 50 plus), despite all training candidates being highly motivated to undertake training (Karpinska *et al.*, 2015). Our results are important in light of the empirical evidence that older workers are less likely to undertake training (e.g. Oosterbeek, 1996; Bassanini *et al.*, 2007). Managers' reluctance to offer training may be an important mechanism in driving the age-profile of work-related training that we often observe.

Finally, decision makers are particularly sensitive to the attributes of the choice alternative which directly relate to the riskiness and cost of the training investment. They are more reluctant, for example, to train candidates who are more mobile. Each additional job change in the previous five years decreases the chances a job candidate is selected for training by around 6.5 percentage points. This is consistent with recent evidence that Dutch managers are less willing to train workers in temporary contracts, especially if they are unlikely to have an ongoing attachment to the firm in the future (Poulissen *et al.*, 2021). Decision makers are also more reluctant to choose training options involving general rather than specific training. Specifically, the chances of offering training that is completely transferable to other firms is around 9 percentage points lower than the chances of offering training that is useful only to the current firm. This gap in training offers is much the same (7 percentage points) when training is only partially useful in other firms, suggesting that any degree of transferability may dampen the enthusiasm for offering training. Poulissen *et al.* (2021) reach the same conclusion in the Dutch context. Costs also matter. Decision makers prefer shorter training; each one-day increase in training duration results in a 1.8 percentage point decline in training offers. Increasing the direct costs of training by €1,000 has a similar effect in reducing the likelihood that training is offered.

5.2 Decision Makers' Willingness-to-Pay

We can gain additional insight into decision makers' training choices by estimating their average willingness-to-pay for the attributes that characterize different choice alternatives. For decision maker i, the average willingness-to-pay for attribute x_{il} across all choice sets t corresponds to the ratio of the coefficient of this attribute β_{il} and the price coefficient β_{ip}. In our application, decision makers do not directly pay for the costs of training. Instead, they act as principals making decisions on behalf of their firms, which, in turn, pay the cost of any training offered. Our willingness-to-pay measures will be based on the estimated coefficient of this cost which effectively captures the (dis)utility that decision makers receive when selecting among choice alternatives with different training costs. Like other principal-agent models, our conceptual framework links decision maker utility to firm profits (and costs) through the compensation that they receive.

We use two approaches to estimate willingness-to-pay parameters. First, we adopt the standard approach and derive willingness-to-pay for each characteristic of our choice alternatives as the ratio of the estimated characteristic coefficient to the estimated coefficient on training costs. That is, we calculate willingness-to-pay after estimating our model of decision maker preferences (see equation (3)). Estimation of willingness-to-pay in preference space can result in highly skewed distributions with unrealistic means and standard deviations (Train and Weeks, 2005; Hole and Kolstad, 2012). Consequently, we circumvent this issue by reformulating our model so that estimated coefficients directly represent willingness-to-pay measures (estimation in willingness-to-pay space). These two approaches can produce different results making sensitivity testing important (see Train and Weeks, 2005; Hole and Kolstad, 2012, for a comparison of methods). Column (4) of Table 4 shows the mean results for willingness-to-pay in preference space, while column (5) refers to the results in willingness-to-pay space. In our case, estimation results are very similar using both approaches. Hence, we focus our discussion on willingness-to-pay in the preference space.

There are several insights. First, in making training offers, decision makers are sensitive to choosing those workers who are likely to benefit from training. They are willing to sacrifice a large share of their budget to send young people (€5,800) and workers with above average occupational expertise ($\sim$ €6,200) to training. In contrast, they are prepared to spend only €420 of their budget to train a woman rather than a man. Second, decision makers are sensitive to the costs of training. Their average willingness-to-pay for training that is one day shorter is on average around €230. This is virtually the same as the daily cost of training (€250) itself even though in approximately two-thirds of the training scenarios firms pay none or only half of the training costs. Third, decision makers are on average unwilling to pay for those attributes of choice alternatives that increase turnover risk. The mean willingness-to-pay for training that is completely transferable to other firms is negative and sizable (€-3,700). The same is true for training for workers with prior job mobility. In fact, training a worker who has changed employers within the last five years implies, on average, the same utility loss for decision makers as a reduction in the budget by around €3,250.

These estimates of decision makers' willingness-to-pay are helpful in quantifying the importance that different dimensions of the choice environment have for the training decisions that are made. The unwillingness of decision makers to train mobile workers and to provide general training is strong evidence that they are sensitive to turnover risk when making training investment decisions.

5.3 The Role of Decision Maker Risk Preferences

Thus far, we have accounted for decision makers' risk preferences by estimating mixed logit specifications that model unobserved individual-specific heterogeneity using random effects. In this subsection, we expand on this by quantifying the extent to which decision makers' risk preferences shape the specific training offers they make. We do this by re-estimating our results using specifications that allow the observed attributes of choice alternatives to be fully interacted with our standardized, continuous measure of decision makers' risk aversion. Results are reported in Table 5. For simplicity, decision makers' risk aversion enters through shifts in the means of the random coefficients; standard deviations are independent of risk aversion. This implies that we estimate the same number of random coefficients as previously. As before, we will focus our discussion on results based on normally distributed cost parameters.[20]

[Insert Table 5 here]

The baseline model in equation (3) is a nested version of the model estimated here. Therefore, we can conduct a likelihood-ratio test for the joint significance of the interaction effects using the results presented in Table 3 and Table 5. We find that, overall, decision makers with different levels of risk preferences do indeed have different preferences for the observed attributes of training alternatives.[21] There is no heterogeneity in decision makers' preferences for the demographic and human capital attributes of training candidates; risk-averse and risk-tolerant decision makers have the same preferences for training female, older and workers with more occupational expertise.[22] Nor is there any indication that decision makers' risk preferences influence their preferences regarding training costs, i.e., the cost-sharing rule and the length of training.

Decision makers' risk preferences are related, however, to those attributes of training alternatives that are most directly related to turnover risk. While there is no evidence of a significant interaction between decision makers' risk preferences and candidates' prior job mobility in the results presented in Table 5, in specifications with correlated random effects we find that less risk-averse managers are less sensitive to job candidates' prior job changes (see Table A.3 in the Appendix). Moreover, we find strong evidence for heterogeneous preferences regarding the transferability of the human capital created during training. Risk-tolerant decision makers are much more likely to offer general training that is either partially or completely transferable to other firms. A one standard deviation increase in a decision maker's measured risk aversion results in a 37 percent decrease in the estimated coefficient for fully transferable training, and a 31 percent decrease in the estimated coefficient for partially transferable training.

We can quantify the economic importance of risk preferences for training offers by comparing the way that risk-averse and risk-tolerant decision makers respond to the different attributes of various choice alternatives. Specifically, we first calculate marginal effects assuming that the decision maker has risk preferences which correspond to the sample average increased by half a standard deviation (i.e. risk-tolerant). Second, we calculate marginal effects assuming that the decision maker has risk preferences equal to the sample mean reduced by half a standard deviation (i.e. risk-averse). Results are reported in Table 6 for those attributes with significant interaction effects, i.e., the transferability of training. We find that risk-averse decision makers

[20] We obtain very similar results when we focus on the cost sharing rule or use a log-normal distribution. See the robustness discussion in Section 5.4.

[21] The test-statistic is 23.1 with 12 degrees of freedom, which corresponds to a p-value of 0.017.

[22] This also holds in a specification with correlated random effects.

are 10.4 percentage points less likely to offer training if it can be fully transferred to other firms than if it cannot be transferred at all. In contrast, risk-tolerant decision makers have a likelihood of offering general training that is only 7.3 percentage points lower, which corresponds to a 30 percent reduction in the response to training transferability. The picture is similar for training that is only partly transferable. The marginal effect drops from 8 percentage points to around 6 percentage points as decision makers move from being risk-averse to risk-tolerant, which corresponds to a 25 percent lower marginal effect. As before, these differential responses associated with decision maker risk preferences can also be expressed in terms of willingness-to-pay. Specifically, we can calculate the extra-willingness-to-pay for decision makers who are less risk-averse. With respect to training that is completely usable in other firms, this extra-willingness-to-pay amounts to ∼€ 1,375 and with respect to training that is partly usable in other firms it is still ∼€ 910.

[Insert Table 6]

Thus, risk-averse decision makers are less likely than their risk-tolerant counterparts to offer training that is general rather than specific. They may also be more sensitive to workers' previous job mobility when deciding who to train. Together, these results indicate that risk aversion leads decision makers to be more sensitive to the potential for worker turnover to reduce the profitability of the training they offer. In contrast, all decision makers – irrespective of their risk preferences – avoid training that is more costly or is targeted towards workers nearing retirement. This is consistent with the risks of training coming largely from the risk that trained workers will leave firm (turnover risk) rather than the risk that the benefits of training do not outweigh the costs (investment risk).

5.4 Robustness Analysis

We consider the robustness of our results to several issues. First, we check whether our results are sensitive to our assumptions about the distribution of the random parameters or to the way we have specified training costs. Specifically, we replicate the marginal effects from Table 4 using different model specifications and present the results in Table A.2. Column (1) reports estimates from a logit model without unobserved heterogeneity and using the cost sharing rules as measures of training costs. Columns (2) and (3) provide marginal effects from a mixed logit model with uncorrelated and correlated coefficients, again incorporating the cost sharing rules. Column (4) shows the results for the mixed logit model with uncorrelated coefficients and log-normally distributed parameter for direct costs. We find that our results are qualitatively the same across all specifications.

This is also true when we consider the sensitivity of our interaction models. These results, presented in Tables A.3 and A.4, essentially replicate our preferred results in Tables 5 and 6. It is noteworthy, though, that we find a significant interaction effect between decision makers' risk preferences and candidates' prior job mobility in column (2) for the correlated model. Less risk-averse managers are less sensitive to job candidates' prior job changes when we use a specification with correlated random effects. Overall, the evidence from these alternative specifications suggests that our main results are not driven by specific parametric assumptions about the distribution of the unobserved heterogeneity nor by the specification of the cost parameters.

Second, we investigate whether our conclusions, based on a continuous measure of decision maker risk preferences, are robust to an alternative specification in which we split the sample into risk-averse and risk-tolerant decision makers. Specifically, we use a binary indicator "Risk-High" which is equal to one if decision makers have risk preferences that are greater than the sample median, and zero otherwise. This indicator is then interacted with the observed attributes of our choice alternatives. The results, reported in Table A.5, are very similar to our preferred results (see Table 5). The only exception worth mentioning is that the interaction with "average occupational expertise" is now also significant.

Third, decision makers differ not only in terms of their risk aversion, but also in other observed and unobserved attributes. Although we cannot account for unobserved heterogeneity, we can control for an array of decision makers' observed attributes using the richness of our data. In particular, we observe standard demographic attributes like gender, education, and tenure, but also non-cognitive skills (Big-5 personality traits and locus of control), and firm attributes including the size, the sector, and the coverage by collective agreements. In order to assess, whether our results are sensitive to variation in observed attributes, we re-estimate our mixed logit model using weights that are constructed to equalize the distributions of observed attributes among risk-averse and risk-tolerant managers.[23] As we do not observe these attributes for all decision makers, the sample becomes slightly smaller. Therefore, we replicate our main results from Table 5 for the smaller sample in column (1) of Table A.7 and find that they are nearly identical. The results for the weighted model are then reported in column (2). The results suggest that the estimated differences between more and less risk-averse managers are not driven by differences in other observed attributes. In fact, if anything, the interaction effects in the weighted model are even more pronounced.

[23] The corresponding propensity score estimation and the differences in observed attributes with and without weights are reported in Table A.6 in the Appendix.

6 Conclusions

A firm's performance rests on the countless decisions of its managers. Measuring how managers actually drive firm outcomes is challenging, however, and previous studies have had little to say about the mechanisms linking managers to organizational performance (Bertrand and Schoar, 2003; Lazear *et al.*, 2015; Hoffman and Tadelis, 2021). We contribute to opening this black box by examining how managers' risk attitudes influence their allocation of employment-related training opportunities. Training decisions are not only consequential for firms, they are also both risky and salient for the human resource managers and firm owners we study. Our conceptual framework considers both the investment and turnover risk of training, linking managers' risk preferences to firms' training decisions through the bonuses they expect to receive. Exogenous variation in the chances that training will be profitable – and hence, in the risk that managers face – is generated using a vignette study design.

Our key finding is that risk-tolerant and risk-averse decision makers have significantly different preferences for the different attributes characterizing training choices. Importantly, risk-tolerant decision makers are less sensitive to turnover risk, i.e. the chances that trained workers will subsequently leave the firm, when making their training choices. They are substantially more likely to offer general training that is either partially or completely transferable to other firms. And, in some specifications, we also find that they are less likely to withhold training from workers with a history of job mobility. In contrast, all decision makers – irrespective of their risk preferences – are sensitive to the investment risk associated with training and avoid training that is more costly or targeted towards workers nearing retirement or those with less occupational expertise. Finally, managers have a slight preference for training women which is at odds with the traditional argument that women's greater propensity to quit reduces the returns to providing them with specific training (e.g. Viscusi, 1980).

Taken together, our results indicate that managers' risk preferences affect firms' investments in employment-related training through heterogeneity in responses to the risk that trained workers will subsequently leave the firm (turnover risk) rather than the risk that the benefits of training do not outweigh the costs (investment risk).

There are two key insights for policies targeting employment-related training. First, evidence that certain workers, in particular those who are less skilled, receive less training has led to calls for expanded access to training as a way of reducing social and economic inequality and promoting social inclusion (see International Labour Organization, 2008, p. vi, for example). Our research highlights that the issue may not simply be some workers' reluctance to engage in training. Managers' reluctance to offer training likely contributes to the training gaps we observe. Policies targeting increased training among under-represented groups need to be sensitive to managers' motivations for offering training. Second, although the conceptual links between workers' job mobility and firms' training investments have long been understood, there has been little empirical evidence on how firms' training decisions play out at an operational level. Our research demonstrates that human resource managers and CEOs are indeed focused on the potential for worker turnover to undermine the training investments they make. This is particularly true if they are risk-averse themselves. Designing contracts that impose penalties for premature quitting and reduce the incentives for poaching by other firms may be effective strategies for increasing firms' training investments (see also Hoffman and Burks, 2017; Almeida *et al.*, 2012).

Studying human resource managers and CEOs in an experimental setting, as we have done here, provides valuable insights into the way that managers' attitudes towards risk affect the decisions they make. This extends the existing experimental literature that is almost exclusively based on samples of university students (Barr and Hitt, 1986). At the same time, ours is a vignette study which has the inherent limitation that participants are asked to make hypothetical choices which may not always correspond to the choices they make in practice (Pager and Quillian, 2005). Complementary research investigating the consequences of managers' risk preferences in real-world settings would be valuable.

In our view, three avenues of research would be particularly fruitful. Our study implicitly focuses on downside risk; participants were not confronted with training scenarios that varied in upside risk (e.g. with respect to productivity gains). Thus, there is no risk associated with the opportunity cost of failing to fully capture the productivity gains to training. Investigating managers' differential responses to upside and downside risk would be particularly interesting in light of previous evidence that managers do not view uncertainty over positive outcomes as an important source of risk (March and Shapira, 1987). Second, firms' return to their training investments is highly variable (Bartel, 2000); it is an open question whether this variability can be linked to differences in the training decisions that risk-tolerant and risk-averse managers make. Finally, there is little doubt that managers can make a substantial contribution to firm performance. Lazear *et al.* (2015) estimate, for example, that moving a boss from the bottom 10 percent to the top 10 percent of the productivity distribution raises productivity as much as adding an extra worker. It would be interesting to understand the role that risk preferences play in that productivity gain.

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Tables and Figures

Table 1: Proportional Frequencies and Choices Made

Attributes	Alternatives Mean (1)	Decisions Mean (2)
Training Candiate:		
Male	0.50	0.48
Female	0.50	0.52
Age		
25 Years Old	0.25	0.28
35 Years Old	0.25	0.28
45 Years Old	0.25	0.25
55 Years Old	0.25	0.19
Occupational Expertise		
Below Average Occ. Expertise	0.33	0.26
Average Occ. Expertise	0.33	0.34
Above Average Occ. Expertise	0.34	0.40
Nr. of Times Changed Employer		
Never Changed Employer	0.33	0.41
1 Time Changed Employer	0.33	0.33
2 Times Changed Employer	0.34	0.26
Training Context:		
Usability in other Firms		
Only Usable in Firm	0.32	0.37
Partly Usable in other Firms	0.34	0.32
Completely Usable in other Firms	0.34	0.30
Training Duration		
Takes 2 Working Days	0.34	0.37
Takes 5 Working Days	0.33	0.34
Takes 10 Working Days	0.33	0.29
Cost Coverage by the Employer		
0 Percent Covered by Employer	0.34	0.35
50 Percent Covered by Employer	0.33	0.34
100 Percent Covered by Employer	0.33	0.32
Observations	12,678	6,339

Note: Source: BIBB-CBS 2017/2018, own calculations.

Table 2: Descriptives of Background Variables

	Mean (1)	SD (2)	Min (3)	Max (4)
Male	0.57	0.50	0	1
Firm Position:				
Owner	0.36	0.48	0	1
CEO	0.13	0.34	0	1
Department Head	0.07	0.25	0	1
Head HR	0.17	0.37	0	1
Head Commerce	0.09	0.28	0	1
Head of Training	0.07	0.26	0	1
Other Position	0.11	0.32	0	1
Educational Status:				
No Vocational Training	0.01	0.08	0	1
Vocational Training	0.20	0.40	0	1
Advanced Vocational Degree	0.35	0.48	0	1
Academic Degree	0.44	0.50	0	1
Firm Tenure in Years	14.42	10.49	0	51
Risk-Affinity (Scale 0-10)	5.46	2.15	0	10
Risk-High[a]	0.36	0.48	0	1
Number of Employees	163.90	1057.46	1	29,000
Share of Small Firms (1-49)	0.70			
Share of Large Firms (50+)	0.30			
Export Oriented[a]	0.10	0.30	0	1
High Competition[a]	0.68	0.47	0	1
Observations	1,060			

Note: Source: BIBB-CBS 2017/2018, own calculations.

[a] Risk-High is defined as a binary variable, that takes the value 1, if the decision maker reports a risk-tolerance above the sample median, i.e. a risk-tolerance above 6, and a value of 0 otherwise.

[b] For these variables the number of observations is slightly lower due to item non-response.

Table 3: Parameter Estimates for Logit and Mixed Logit Models

	Model				
	Logit	Mixed Logit	Mixed Logit Correlated	Mixed Logit Direct Costs	Mixed Logit Direct Costs Ln
	(1)	(2)	(3)	(4)	(5)
Mean:					
Training Candidate:					
Female	0.072**	0.076*	0.092*	0.061*	0.064*
	(0.029)	(0.038)	(0.052)	(0.038)	(0.038)
Age					
25 Years Old	0.640***	0.842***	1.240***	0.856***	0.860***
	(0.052)	(0.072)	(0.118)	(0.070)	(0.070)
35 Years Old	0.598***	0.805***	1.172***	0.822***	0.823***
	(0.051)	(0.071)	(0.116)	(0.071)	(0.071)
45 Years Old	0.499***	0.654***	0.918***	0.655***	0.659***
	(0.050)	(0.068)	(0.103)	(0.066)	(0.066)
55 Years Old	Ref.				
Occupational Expertise					
Above Average	0.665***	0.927***	1.335***	0.914***	0.922***
	(0.051)	(0.072)	(0.125)	(0.069)	(0.069)
Average	0.389***	0.502***	0.783***	0.491***	0.493***
	(0.042)	(0.052)	(0.093)	(0.051)	(0.051)
Below Average	Ref.				
Job Mobility	-0.351***	-0.487***	-0.687***	-0.481***	-0.482***
	(0.021)	(0.033)	(0.055)	(0.032)	(0.032)
Training Context:					
Usability in other Firms					
Completely Useable	-0.413***	-0.558***	-0.763***	-0.554***	-0.552***
	(0.041)	(0.055)	(0.084)	(0.053)	(0.053)
Partly	-0.316***	-0.448***	-0.648***	-0.436***	-0.436***
	(0.039)	(0.053)	(0.081)	(0.051)	(0.052)
Only Useable in Firm	Ref.				
Cost Coverage by the Employer					
100 Percent	-0.135***	-0.190***	-0.329***		
	(0.038)	(0.050)	(0.073)		
50 Percent	0.012	0.026	0.023		
	(0.040)	(0.051)	(0.076)		
0 Percent	Ref.				
Training Duration	-0.038***	-0.054***	-0.068***	-0.034***	-0.035***
	(0.005)	(0.007)	(0.011)	(0.008)	(0.008)
Direct Costs (for employer)				-0.149***	-0.149***
				(0.035)	(0.036)
SD:					
Female		0.411***	0.466***	0.420***	0.427***
		(0.091)	(0.117)	(0.088)	(0.087)
Age					
25 Years Old		0.530***	1.245***	-0.452***	-0.493***
		(0.145)	(0.189)	(0.161)	(0.151)
35 Years Old		0.499***	1.233***	0.507***	0.506***
		(0.144)	(0.187)	(0.145)	(0.148)
45 Years Old		-0.320	1.170***	-0.309	-0.288
		(0.205)	(0.204)	(0.205)	(0.213)
Occupational Expertise					
Above Average		1.174***	2.370***	1.152***	1.163***
		(0.089)	(0.188)	(0.086)	(0.087)
Average		-0.078	1.318***	-0.004	0.005
		(0.183)	(0.139)	(0.172)	(0.178)
Job Mobility		0.362***	0.489***	0.356***	0.369***
		(0.058)	(0.079)	(0.057)	(0.055)
Usability in other Firms					
Completely		-0.288	0.964***	0.305	0.255
		(0.155)	(0.155)	(0.162)	(0.188)
Partly		-0.151	0.931***	0.100	0.073

		(0.173)	(0.138)	(0.213)	(0.228)
Cost Coverage by the Employer					
100 Percent		0.033	0.804***		
		(0.211)	(0.151)		
50 Percent		-0.195	0.817***		
		(0.249)	(0.146)		
Training Duration		0.097***	0.132***	0.094***	0.096***
		(0.014)	(0.019)	(0.013)	(0.013)
Direct Costs (for employer)				0.022	0.037
				(0.158)	(0.196)
Observations	12,678	12,678	12,678	12,678	12678
Log-Likelihood	-3895	-3802	-3686	-3804	-3804
Number of Draws		300	300	300	300
Degrees of Freedom	12	24	90	77	77
AIC	7815	7657	7565	7550	7551
BIC	7904	7835	8235	8124	8124

Note: Standard errors in parentheses. Source: BIBB-CBS 2017/2018, own calculations. ***/**/* indicate statistical significance at the 1%/5%/10%-level. Estimation based on 300 scrambled Halton draws.

Table 4: Marginal Effects and Willingness-to-Pay (in €)

	Marginal Effects	Willingness-to-Pay (in €)	
	Mixed Logit Direct Costs (1)	Pref. Space (2)	WTP-Space (3)
Training Candidate:			
Female	0.0085	416.17	452.79
	(0.057)	(278.08)	(286.98)
Age			
25 Years Old	0.1335**	5,797.54***	5,880.33***
	(0.063)	(1,400.71)	(1,452.69)
35 Years Old	0.1275*	5,553.43***	5,631.44***
	(0.066)	(1,337.66)	(1,381.06)
45 Years Old	0.1050***	4,433.84***	4,543.92***
	(0.040)	(1,117.47)	(1,169.79)
Occupational Expertise			
Average	0.0860***	3,306.67***	3,579.00***
	(0.006)	(844.44)	(948.25)
Above Average	0.1311	6,199.69***	6,465.08***
	(0.141)	(1,501.69)	(1,606.13)
Job Mobility	-0.0641	-3,252.46***	-3,334.07***
	(0.039)	(778.43)	(815.41)
Training Context:			
Usability in other Firms			
Partly	-0.0718***	-2,937.83***	-2,939.08***
	(0.012)	(768.17)	(784.72)
Completely	-0.0911**	-3,710.20***	-3,814.00***
	(0.036)	(940.96)	(986.27)
Training Duration	-0.0176	-232.80**	-235.23**
	(0.012)	(97.07)	(100.06)
Direct Costs (for employer)	-0.0188*		
	(0.011)		

Note: Column (1) shows the average marginal effects corresponding to the mixed logit model with direct costs (see column (4) in Table 3). Columns (2) and (3) display the willingness-to-pay (in €) based on a fixed direct cost coefficient and an estimation in the WTP-Space.
***/**/* indicate statistical significance at the 1%/5%/10%-level.

Table 5: Parameter Estimates for Mixed Logit Model with Interaction

	Interacted Model
	Mixed Logit Direct Cost (1)
Mean:	
Training Candidate:	
Female	0.066*
	(0.038)
Age	
25 Years Old	0.867***
	(0.070)
35 Years Old	0.828***
	(0.071)
45 Years Old	0.663***
	(0.066)
Occupational Expertise	
Above Average	0.920***
	(0.069)
Average	0.495***
	(0.051)
Job Mobility	-0.480***
	(0.032)
Training Context:	
Usability in other Firms	
Completely	-0.553***
	(0.053)
Partly	-0.433***
	(0.052)
Training Duration	-0.035***
	(0.008)
Direct Costs (for employer)	-0.153***
	(0.036)
Interacted with RISK by:	
Training Candidate:	
Female	0.015
	(0.038)
Age	
25 Years Old	-0.061
	(0.064)
35 Years Old	-0.014
	(0.065)
45 Years Old	-0.031
	(0.063)
Occupational Expertise	
Above Average	-0.035
	(0.062)
Average	-0.071
	(0.049)
Job Mobility	0.038
	(0.028)
Training Context:	
Usability in other Firms	
Completely	0.205***
	(0.051)
Partly	0.134***
	(0.049)
Training Duration	-0.005
	(0.008)
Direct Costs (for employer)	-0.014
	(0.036)
SD	
Female	0.438***

	(0.086)
Age	
25 Years Old	-0.469***
	(0.157)
35 Years Old	0.508***
	(0.148)
45 Years Old	-0.291
	(0.213)
Professional Competency	
Above Average	1.163***
	(0.088)
Average	0.014
	(0.175)
Job Mobility	0.361***
	(0.056)
Usability in other Firms	
Completely	0.229
	(0.213)
Partly	0.073
	(0.245)
Training Duration	0.096***
	(0.013)
Direct Costs (for employer)	-0.001
	(0.139)
Observations	12,678
Log-Likelihood	-3,793
Number of Draws	300
LR test statistic	23.11
p-value	0.017

Note: Standard errors in parentheses. Source: BIBB-CBS 2017/2018, own calculations. ***/**/* indicate statistical significance at the 1%/5%/10%-level.
Estimation based on 300 scrambled Halton draws.

Table 6: Marginal Effects for Mixed Logit Model with Interaction

	Interacted Model (Marginal Effects)
	Mixed Logit Direct Costs (1)
Risk-tolerant decision makers	
Partly	-0.0595***
	(0.007)
Completely	-0.0728***
	(0.017)
Risk-averse decision makers	
Partly	-0.0795***
	(0.007)
Completely	-0.1043***
	(0.019)

***/**/* indicate statistical significance at the 1%/5%/10%-level.

Figure 1: Vignette Example

Irrespective of the actual situation in your company, please imagine the following scenario:

Two of your skilled workers would like to continue their professional development. For operational reasons, however, only one of the two skilled workers can participate in further education. Which one would you choose?

The two skilled worker differ according to gender, age, occupational experience and occupational mobility. The further training differs with regard to the applicability of acquired competences in your or other companies as well as the training's duration and costs. The skilled worker is released for the duration of the training. The daily rate for course fees and travel costs is €250. With regard to all features not listed, skilled workers and trainings are identical. All information about the two skilled workers and the trainings can be found below.

Please indicate if you would like to train skilled worker 1 or 2.

Profil Skilled worker 1	**Profil Skilled worker 2**
The skilled worker …	*The skilled worker …*
... is female.	… is male.
... is 45 years old.	... is 55 years old.
... has above average occupational experience.	... has average occupational experience.
... 1 time changed employer within the last 5 years.	... never changed employer within the last 5 years.
The training …	*The training …*
... is completely useable also in other firms.	… is partly useable also in other firms.
... takes 5 working days.	... takes 2 working days.
... is covered by 100% of the employer. The participant has no costs.	... is not covered by the employer. 100% of costs are taken over by the participant.

A Supplementary Tables and Figures

Table A.1: Possible Values of Vignette Attributes

Attribute	Attribute Values
	The skilled worker ...
Gender	(1) ... is male. (2) ... is female.
Age	(1) ... is 25 years old. (2) ... is 35 years old. (3) ... is 45 years old. (4) ... is 55 years old.
Occupational Experience	(1) ... has below average occupational experience. (2) ... has average occupational experience. (3) ... has above average occupational experience.
Occupational Mobility	(1) ... never changed employer within the last 5 years. (2) ... 1 time changed employer within the last 5 years. (3) ... 2 times changed employer within the last 5 years.
	The training ...
Content	(1) ... is only useable in your firm and not in other firms. (2) ... is partly useable also in other firms. (3) ... is completely useable also in other firms.
Duration	(1) ... takes 2 working days. (2) ... takes 5 working days. (3) ... takes 10 working days.
Cost Coverage	(1) ... is not covered by the employer. 100% of costs are taken over by the participant. (2) ... is covered by 50% of the employer. The participant takes over the remaining 50% of the costs. (3) ... is covered by 100% of the employer. The participant has no costs.

Table A.2: Robustness Analysis 1a: Distribution of Random Parameters and Cost Specification

	Model (Marginal Effects)			
	Conditional Logit (1)	Mixed Logit (2)	Mixed Logit Correlated (3)	Mixed Logit Direct Costs Ln (4)
Training Candidate:				
Female	0.0167**	0.0107***	0.0087***	0.0088**
	(0.007)	(0.001)	(0.002)	(0.004)
Age				
25 Years Old	0.1505***	0.1289***	0.1290***	0.1330***
	(0.012)	(0.008)	(0.006)	(0.007)
35 Years Old	0.1406***	0.1240***	0.1260***	0.1273***
	(0.012)	(0.008)	(0.006)	(0.006)
45 Years Old	0.1174***	0.1039***	0.1029***	0.1055***
	(0.012)	(0.008)	(0.005)	(0.004)
Occupational Experience				
Average	0.0916***	0.0866***	0.0836***	0.0862***
	(0.009)	(0.006)	(0.005)	(0.002)
Above Average	0.1564***	0.1310***	0.1165***	0.1315***
	(0.012)	(0.009)	(0.006)	(0.012)
Job Mobility	-0.0826***	-0.0640***	-0.0648***	-0.0639***
	(0.005)	(0.002)	(0.003)	(0.003)
Training Context:				
Usability in other Firms				
Partly	-0.0742***	-0.0728***	-0.0798***	-0.0713***
	(0.009)	(0.003)	(0.004)	(0.002)
Completely	-0.0971***	-0.0906***	-0.0922***	-0.0902***
	(0.009)	(0.004)	(0.004)	(0.003)
Training Duration	-0.0090***	-0.0284***	-0.0273***	-0.0180***
	(0.002)	(0.001)	(0.001)	(0.009)
Cost Coverage by the Employer				
50 Percent	0.0027	0.0038***	0.0024	
	(0.009)	(0.001)	(0.002)	
100 Percent	-0.0318***	-0.0303***	-0.0368***	
	(0.009)	(0.001)	(0.002)	
Direct Costs (for employer)				-0.0188***
				(0.004)

Note: The displayed values in column (1) are the average marginal effects of the basic conditional logit model corresponding to column (1) in Table 3. Column (2) shows the average marginal effects corresponding to the basic mixed logit model (see column (2) in Table 3). The average marginal effects in column (3) correspond to the mixed logit model with correlated effects (see column (3) in Table 3). Column (4) shows the average marginal effects of the mixed logit model with log-normal distributed direct cost coefficient, corresponding to column (5) in Table 3.
***/**/* indicate statistical significance at the 1%/5%/10%-level.

Table A.3: Robustness Analysis 1b: Distribution of Random Parameters and Cost Specification for Interacted Models (Parameter Estimates)

	Interacted Model		
	Mixed Logit	Mixed Logit Correlated	Mixed Logit Direct Cost Ln
	(1)	(2)	(3)
Mean:			
Training Candidate:			
Female	0.078**	0.085	0.066*
	(0.038)	(0.055)	(0.038)
Age			
25 Years Old	0.850***	1.260***	0.867***
	(0.072)	(0.127)	(0.070)
35 Years Old	0.811***	1.178***	0.828***
	(0.072)	(0.126)	(0.071)
45 Years Old	0.657***	0.936***	0.663***
	(0.068)	(0.108)	(0.066)
Occupational Experience			
Above Average	0.925***	1.319***	0.920***
	(0.072)	(0.130)	(0.069)
Average	0.503***	0.756***	0.495***
	(0.052)	(0.094)	(0.051)
Job Mobility	-0.486***	-0.683***	-0.480***
	(0.033)	(0.059)	(0.032)
Training Context:			
Usability in other Firms			
Completely	-0.559***	-0.782***	-0.553***
	(0.055)	(0.092)	(0.053)
Partly	-0.447***	-0.646***	-0.433***
	(0.053)	(0.084)	(0.052)
Cost Coverage by the Employer			
100 Percent	-0.194***	-0.326***	
	(0.050)	(0.075)	
50 Percent	0.024	0.018	
	(0.051)	(0.081)	
Training Duration	-0.055***	-0.068***	-0.035***
	(0.007)	(0.011)	(0.008)
Direct Costs (for employer)			-0.153***
			(0.036)
Interacted with RISK by:			
Training Candidate:			
Female	0.015	0.006	0.015
	(0.038)	(0.052)	(0.038)
Age			
25 Years Old	-0.060	-0.080	-0.061
	(0.065)	(0.093)	(0.064)
35 Years Old	-0.012	0.002	-0.014
	(0.065)	(0.095)	(0.065)
45 Years Old	-0.032	-0.000	-0.031
	(0.064)	(0.088)	(0.063)
Occupational Experience			
Above Average	-0.035	-0.073	-0.035
	(0.063)	(0.099)	(0.062)
Average	-0.075	-0.107	-0.071
	(0.050)	(0.078)	(0.049)
Job Mobility	0.040	0.081**	0.038
	(0.028)	(0.040)	(0.028)
Usability in other Firms			
Training Context:			
Completely	0.205***	0.310***	0.205***
	(0.052)	(0.076)	(0.051)
Partly	0.136***	0.229***	0.134***
	(0.050)	(0.074)	(0.049)

Training Duration	-0.002	-0.000	-0.005
	(0.007)	(0.009)	(0.008)
Cost Coverage by the Employer			
100 Percent	0.013	0.012	
	(0.050)	(0.071)	
50 Percent	-0.053	-0.071	
	(0.051)	(0.072)	
Direct Costs (for employer)			-0.014
			(0.036)
SD			
Female	0.423***	0.650***	0.438***
	(0.090)	(0.124)	(0.086)
Age			
25 Years Old	0.505***	1.072***	-0.469***
	(0.152)	(0.209)	(0.157)
35 Years Old	0.504***	1.373***	0.508***
	(0.143)	(0.201)	(0.148)
45 Years Old	-0.321	0.926***	-0.291
	(0.207)	(0.178)	(0.213)
Professional Competency			
Above Average	1.177***	2.380***	1.163***
	(0.090)	(0.201)	(0.088)
Average	-0.071	1.321***	0.014
	(0.178)	(0.149)	(0.175)
Job Mobility	0.352***	0.480***	0.361***
	(0.059)	(0.085)	(0.056)
Usability in other Firms			
Completely	-0.287*	1.011***	0.229
	(0.155)	(0.178)	(0.213)
Partly	-0.154	0.915***	0.073
	(0.175)	(0.162)	(0.245)
Cost Coverage by the Employer			
100 Percent	0.035	0.886***	
	(0.204)	(0.146)	
50 Percent	-0.180	0.731***	
	(0.263)	(0.185)	
Training Duration	0.098***	0.138***	0.096***
	(0.014)	(0.022)	(0.013)
Direct Costs (for employer)			0.002
			(0.168)
Observations	12,678	12,678	12,678
Log-Likelihood	-3791	-3677	-3793
Number of Draws	300	300	300

Note: Standard errors in parentheses. Source: BIBB-CBS 2017/2018, own calculations. ***/**/* indicate statistical significance at the 1%/5%/10%-level. Estimation based on 300 scrambled Halton draws.

Table A.4: Robustness Analysis 1c: Distribution of Random Parameters and Cost Specification for Interacted Models (Marginal Effects)

	Interacted Model (Marginal Effects)		
	Mixed Logit	Mixed Logit Correlated	Mixed Logit Direct Costs Ln
	(1)	(2)	(3)
Risk-tolerant decision makers			
Partly	-0.0608***	-0.0617	-0.0593***
	(0.012)	(0.001)	(0.007)
Completely	-0.0733***	-0.0720	-0.0731***
	(0.021)	(0.001)	(0.016)
Risk-averse decision makers			
Partly	-0.0809***	-0.0854	-0.0794***
	(0.013)	(0.001)	(0.006)
Completely	-0.1042***	-0.1050	-0.1042***
	(0.024)	(0.002)	(0.017)

Note: ***/**/* indicate statistical significance at the 1%/5%/10%-level.

Table A.5: Robustness Analysis 2: Interacted Models with Risk.High Dummy (Parameter Estimates)

	Interacted Model with Risk-High Dummy			
	Mixed Logit Direct Costs (1)	Mixed Logit (2)	Mixed Logit Correlated (3)	Mixed Logit Direct Costs Ln (4)
Mean:				
Training Candidate:				
Female	0.025	0.053	0.035	0.025
	(0.047)	(0.069)	(0.048)	(0.047)
Age				
25 Years Old	0.866***	1.304***	0.849***	0.866***
	((0.085)	(0.149)	(0.087)	(0.085)
35 Years Old	0.786***	1.168***	0.772***	0.786***
	((0.085)	(0.145)	(0.086)	(0.085)
45 Years Old	0.651***	0.918***	0.649***	0.651***
	(0.081)	(0.127)	(0.083)	(0.081)
Occupational Experience				
Above Average	0.981***	1.465***	0.989***	0.981***
	(0.083)	(0.153)	(0.086)	(0.083)
Average	0.578***	0.934***	0.588***	0.578***
	(0.063)	(0.116)	(0.065)	(0.063)
Job Mobility	-0.495***	-0.747***	-0.501***	-0.495***
	(0.038)	(0.069)	(0.039)	(0.038)
Training Context:				
Usability in other Firms				
Completely	-0.715***	-1.031***	-0.722***	-0.715***
	(0.067)	(0.113)	(0.069)	(0.067)
Partly	-0.506***	-0.786***	-0.520***	-0.506***
	(0.064)	(0.105)	(0.066)	(0.064)
Cost Coverage by the Employer				
100 Percent		-0.357***	-0.205***	
		(0.095)	(0.063)	
50 Percent		0.019	0.053	
		(0.098)	(0.064)	
Training Duration	-0.033***	-0.073***	-0.054***	-0.033***
	(0.010)	(0.014)	(0.009)	(0.010)
Direct Costs (for employer)	-0.154***			-0.154***
	(0.045)			(0.045)
Interaction with Risk-High by:				
Training Candidate:				
Female	0.107	0.094	0.112	0.107
	(0.078)	(0.107)	(0.078)	(0.078)
Age				
25 Years Old	-0.013	-0.004	-0.015	-0.013
	(0.131)	(0.196)	(0.132)	(0.131)
35 Years Old	0.098	0.160	0.093	0.098
	(0.133)	(0.200)	(0.134)	(0.133)
45 Years Old	0.016	0.126	0.007	0.016
	(0.129)	(0.188)	(0.130)	(0.129)
Occupational Experience				
Above Average	-0.173	-0.279	-0.179	-0.173
	(0.128)	(0.212)	(0.130)	(0.128)
Average	-0.230**	-0.348**	-0.235**	-0.230**
	(0.100)	(0.165)	(0.102)	(0.100)
Job Mobility	0.042	0.103	0.046	0.042
	(0.057)	(0.081)	(0.057)	(0.057)
Training Context:				
Usability in other Firms				
Completely	0.451***	0.697***	0.452***	0.451***
	(0.105)	(0.158)	(0.106)	(0.105)
Partly	0.199*	0.375**	0.200*	0.199*
	(0.102)	(0.150)	(0.103)	(0.102)

Training Duration	-0.005	-0.000	-0.003	-0.005
	(0.017)	(0.019)	(0.014)	(0.017)
100 Percent		0.043	0.038	
		(0.146)	(0.102)	
50 Percent		-0.034	-0.081	
		(0.151)	(0.106)	
Direct Costs (for employer)	-0.010			-0.010
	(0.073)			(0.073)
SD:				
Female	0.423***	0.595***	0.408***	0.423***
	(0.088)	(0.121)	(0.091)	(0.088)
Age				
25 Years Old	-0.464***	1.234***	0.494***	-0.464***
	(0.157)	(0.191)	(0.153)	(0.157)
35 Years Old	0.512***	1.427***	0.506***	0.512***
	(0.145)	(0.200)	(0.141)	(0.145)
45 Years Old	-0.277	1.044***	-0.303	-0.277
	(0.218)	(0.209)	(0.213)	(0.218)
Occupational Experience				
Above Average	1.163***	2.375***	1.175***	1.163***
	(0.087)	(0.193)	(0.089)	(0.087)
Average	0.008	1.352***	-0.072	0.008
	(0.174)	(0.149)	(0.176)	(0.174)
Job Mobility	0.358***	0.509***	0.351***	0.358***
	(0.056)	(0.082)	(0.058)	(0.056)
Usability in other Firms				
Completely	0.212	0.998***	-0.264	0.212
	(0.231)	(0.159)	(0.164)	(0.231)
Partly	0.063	0.957***	-0.139	0.063
	(0.246)	(0.147)	(0.178)	(0.246)
Cost Coverage by the Employer				
100 Percent		0.837***	0.045	
		(0.152)	(0.200)	
50 Percent		0.784***	-0.194	
		(0.163)	(0.250)	
Training Duration	0.096***	0.139***	0.097***	0.096***
	(0.013)	(0.019)	(0.014)	(0.013)
Direct Costs (for employer)	0.000			0.000
	(0.137)			(0.163)
Observations	12678	12678	12678	12678
Log-Likelihood	-3791	-3672	-3788	-3791
Number of Draws	300	300	300	300

Note: Standard errors in parentheses. Source: BIBB-CBS 2017/2018, own calculations.
***/**/* indicate statistical significance at the 1%/5%/10%-level.
Estimation based on 300 scrambled Halton draws.

Table A.6: Robustness Analysis 3a: Propensity Score Estimation and Matching Quality

	Logit Estimation	MSB (%bias)			
	P(Risk-Median = 1)	Unmatched	Matched	t-test	p-value
	(1)	(2)	(3)	(4)	(5)
Firm Position:					
Owner	0.723***	16.5	1.5	0.69	0.491
	(0.100)				
CEO	0.617***	9.0	-4.3	-1.88	0.060
	(0.101)				
Department Head	0.447***	8.2	0.3	0.15	0.880
	(0.112)				
Head HR	0.301***	-0.7	-4.8	-2.20	0.028
	(0.094)				
Head Commerce	-0.163	-13.5	3.3	1.75	0.081
	(0.114)				
Head of Training	-0.440***	-16.1	1.0	0.56	0.573
	(0.120)				
Other Position	Ref.	-17.7	4.5	2.49	0.013
Firm Tenure in Years	-0.015***	-9.7	-1.0	-0.46	0.643
	(0.002)				
Educational Status:					
No Vocational Degree	1.031***	4.4	-2.1	-0.84	0.401
	(0.271)				
Vocational Degree	0.009	-1.5	3.1	1.44	0.149
	(0.063)				
Advanced Voc. Degree	-0.020	-4.0	-0.5	-0.22	0.828
	(0.055)				
Academic Degree	Ref.	4.4	-1.7	-0.79	0.431
Firm's Training Decision:					
Alone	0.083	16.1	1.1	0.48	0.632
	(0.107)				
Together	0.006	-5.5	2.2	1.02	0.309
	(0.098)				
Support	0.269***	-3.0	-4.5	-2.08	0.037
	(0.102)				
Not Involved	Ref.	-13.5	0.2	0.13	0.900
Reciprocity	-0.060***	-1.3	6.8	3.01	0.003
	(0.019)				
Internal Locus of Control	0.427***	34.1	10.2	5.02	0.000
	(0.034)				
Big Five:					
Openness	0.449***	50.6	-1.9	-0.93	0.351
	(0.025)				
Conscientiousness	-0.150***	3.8	6.7	3.05	0.002
	(0.030)				
Extraversion	0.341***	52.7	1.9	0.93	0.354
	(0.022)				
Agreeableness	-0.413***	-23.2	3.3	1.48	0.138
	(0.026)				
Emotional Stability	0.187***	27.7	6.5	3.16	0.002
	(0.021)				
Number of Employees in Firm	0.000	-3.7	0.5	0.28	0.782
	(0.000)				
Vocational Training Provider	-0.066	-5.7	-1.3	-0.59	0.558
	(0.051)				
Firm:					
Export-oriented	0.591***	12.7	2.9	1.28	0.202
	(0.079)				
High Competition	0.005	1.4	-2.1	-0.97	0.330
	(0.050)				
Training Cooperations	-0.025	8.9	-2.0	-0.91	0.364

	(0.052)				
Profit Sharing	0.115**	12.5	2.4	1.09	0.274
	(0.049)				
Flexible Work Hours	0.320***	10.5	-1.2	-0.55	0.584
	(0.049)				
Firmtype:					
Autonomous Individual Holding	-0.015	3.1	-0.7	-0.31	0.756
	(0.121)				
Independent Operation as Part of Enterprise	0.359***	5.6	-1.1	-0.49	0.623
	(0.134)				
Corporate Headquarter	-0.137	-5.2	-3.1	-1.47	0.140
	(0.143)				
Branch Office	0.513***	6.2	4.4	2.01	0.044
	(0.139)				
Foundation, Institution, Authority	-0.641***	-11.0	1.1	0.60	0.549
	(0.199)				
Something Different	Ref.	-7.7	-0.0	-0.01	0.992
Firm's Utilized Capacity	-0.006***	-2.7	-0.4	-0.19	0.850
	(0.002)				
Firm Sector:					
Agriculture (A)	0.173	-3.0	0.1	0.04	0.966
	(0.188)				
Manufacturing (C)	0.436***	6.7	3.0	1.37	0.172
	(0.108)				
Water Supply (E)	-0.128	-5.3	-0.5	-0.27	0.785
	(0.354)				
Construction (F)	0.545***	0.8	-4.9	-2.18	0.029
	(0.109)				
Wholesale, Retail Trade (G)	0.454***	1.5	2.3	1.09	0.274
	(0.096)				
Transportation (H)	0.068	-5.3	-1.3	-0.65	0.517
	(0.149)				
Accommodation Activities (I)	0.463***	9.8	-5.1	-2.12	0.034
	(0.114)				
Information Activities (J)	0.485***	2.9	-4.6	-1.97	0.049
	(0.133)				
Finance and Insurance (K)	0.470***	7.4	3.1	1.35	0.176
	(0.158)				
Real Estate Activities (L)	0.106	-7.5	-1.2	-0.65	0.516
	(0.201)				
Professional Activities (M)	0.295***	-5.6	1.7	0.86	0.393
	(0.109)				
Administrative Activities (N)	0.397***	3.3	6.3	2.99	0.003
	(0.114)				
Public Administration (O)	1.491***	-1.5	1.4	0.66	0.509
	(0.214)				
Education (P)	-0.479*	-13.2	0.6	0.42	0.676
	(0.252)				
Human Health, Social Work (Q)	0.332***	-2.8	-2.2	-1.03	0.304
	(0.101)				
Arts, Recreation (R)	0.201	0.4	4.6	2.45	0.014
	(0.256)				
Other service Activities (S)	0.001	-0.3	-0.7	-0.33	0.741
	(0.122)				
Other Branches (inl. Mining B, Electricity C)	Ref.	-3.0	-0.1	-0.07	0.948
Work Council	-0.307***	-10.9	2.1	1.03	0.303
	(0.069)				
Collective Bargaining Coverage	0.339***	4.9	-2.3	-1.06	0.289
	(0.051)				
Constant	-8.766***				
	(1.188)				
Observations	11,842				

Sample	Ps R2	LR chi2	p>chi2	Mean Bias	B
Unmatched	0.147	2290.56	0.00	9.3	96.3
Matched	0.010	114.55	0.00	2.5	23.1

Note: Source: BIBB-CBS 2017/2018, own calculations. Standard errors in parentheses. ***/**/* indicate statistical significance at the 1%/5%/10%-level.

The mean standardized bias (MSB) is reported before matching in column (2) and after matching in column (3). The *t*-test statistics in column (4) and the complementary *p*-values in column (5) correspond to a *t*-test for equality of means in the two samples, before and after matching.

The summary statistics contain for both the unmatched sample and the matched sample the Pseudo R^2 values in column (1), the test statistics for the likelihood ratio test on the joint significance of all regressors in column (2) and the corresponding *p*-values in column (3), the mean biases in column (4), and Rubin's B estimates in column (5).

Table A.7: Robustness Analysis 3b: Parameter Estimates of Mixed Logit Model with Interaction with and without Weights

	Interacted Model	
	Mixed Logit Direct Costs Unweighted	Mixed Logit Direct Costs Weighted
Mean:		
Training Candidate:		
Female	0.065	0.099*
	(0.040)	(0.056)
Age		
25 Years Old	0.877***	0.994***
	(0.075)	(0.104)
35 Years Old	0.830***	0.916***
	(0.075)	(0.104)
45 Years Old	0.667***	0.760***
	(0.069)	(0.097)
Occupational Experience		
Above Average	0.961***	1.020***
	(0.073)	(0.112)
Average	0.505***	0.526***
	(0.054)	(0.076)
Job Mobility	-0.500***	-0.578***
	(0.035)	(0.053)
Training Context:		
Usability in other Firms		
Completely	-0.525***	-0.669***
	(0.055)	(0.078)
Partly	-0.428***	-0.534***
	(0.054)	(0.072)
Training Duration	-0.034***	-0.030***
	(0.009)	(0.011)
Direct Costs (for employer)	0.150***	0.161***
	(0.038)	(0.056)
Interacted with RISK by:		
Training Candidate:		
Female	0.033	0.019
	(0.040)	(0.057)
Age		
25 Years Old	-0.042	-0.117
	(0.068)	(0.098)
35 Years Old	0.002	-0.051
	(0.069)	(0.097)
45 Years Old	-0.017	-0.098
	(0.065)	(0.095)
Occupational Experience		
Above Average	-0.046	-0.168*
	(0.064)	(0.098)
Average	-0.075	-0.121*
	(0.052)	(0.070)
Job Mobility	0.051*	0.107***
	(0.029)	(0.040)
Training Context:		
Usability in other Firms		
Completely	0.187***	0.291***
	(0.053)	(0.070)
Partly	0.143***	0.209***
	(0.052)	(0.064)
Training Duration	-0.005	-0.005
	(0.009)	(0.010)
Direct Costs (for employer)	-0.021	-0.022
	(0.037)	(0.052)
SD:		

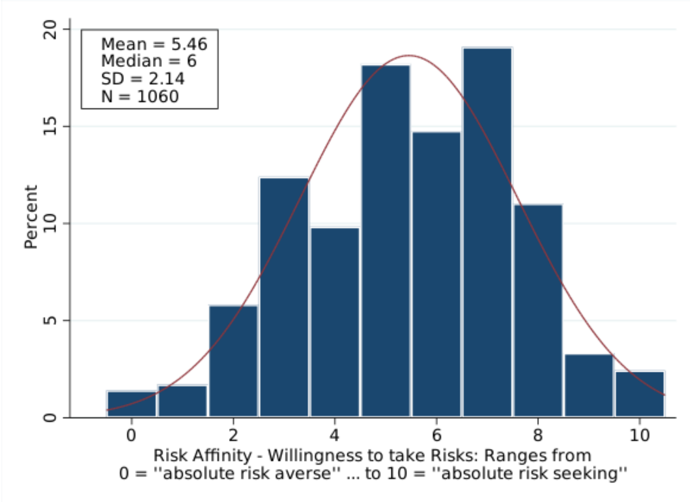
Female	0.447***	0.494***
	(0.089)	(0.113)
Age		
25 Years Old	0.500***	0.434*
	(0.163)	(0.264)
35 Years Old	0.591***	0.657***
	(0.142)	(0.165)
45 Years Old	0.112	0.093
	(0.356)	(0.133)
Occupational Experience		
Above Average	1.174***	1.178***
	(0.092)	(0.116)
Average	-0.156	-0.200
	(0.146)	(0.148)
Job Mobility	0.395***	0.445***
	(0.055)	(0.070)
Usability in other Firms		
Completely	0.223	0.350**
	(0.199)	(0.175)
Partly	0.113	-0.133
	(0.236)	(0.206)
Training Duration	0.098***	0.096***
	(0.014)	(0.018)
Direct Costs (for employer)	-0.092	-0.175*
	(0.125)	(0.104)
Observations	11,842	11,842
Log-Likelihood	-3537	-2547
Number of Draws	300	300

Note: Standard errors in parentheses. Source: BIBB-CBS 2017/2018, own calculations. ***/**/* indicate statistical significance at the 1%/5%/10%-level. Estimation based on 300 scrambled Halton draws.

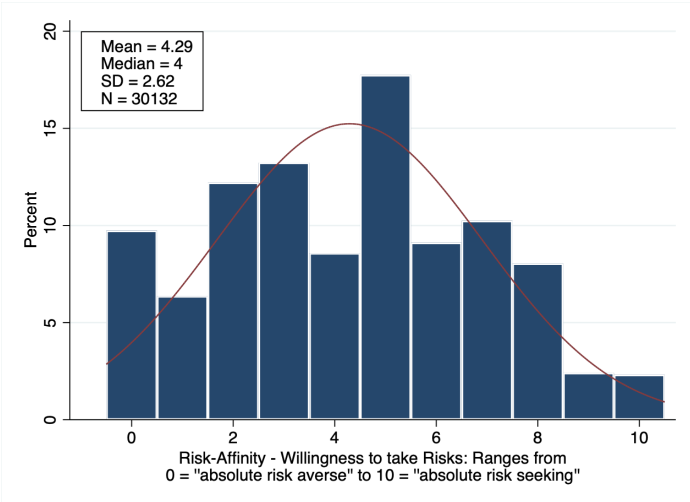
Column (1) replicates the analysis from Table 5 for those where the conditioning variables are not missing. The sample drops by 836 observations

Figure A.1: Distribution of Risk Tolerance in Our Sample and the German Population

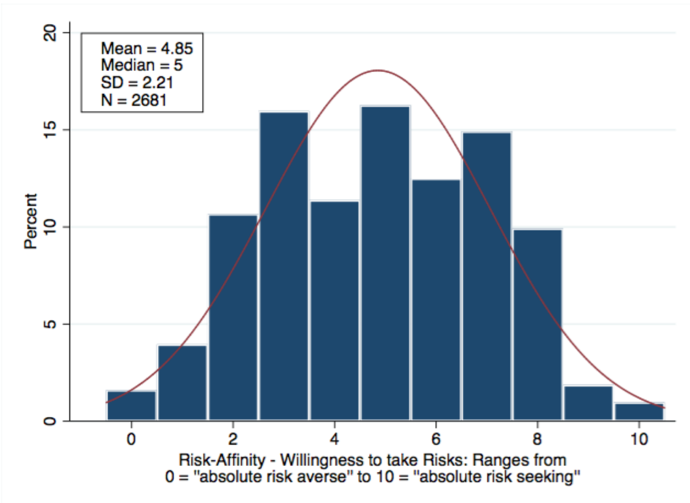
A. Our Sample



B. SOEP



C. SOEP - Decision Makers



Note: Figure A illustrates the distribution of risk tolerance in our sample. Figure B displays the distribution of risk tolerance of individuals who participated in the SOEP in 2018. Figure C shows the distribution of risk tolerance of individuals who participated in the SOEP in 2018 and occupied a job in a leading position.