

Managers' risk preferences and firm training investments[☆]

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ABSTRACT

This study analyses the impact of managers' risk preferences on their training allocation decisions. We begin by providing nationally representative evidence that managers' risk-aversion is negatively correlated with the likelihood that their firms engage in any worker training. Using a novel vignette study, we then demonstrate that 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 less general training and are more reluctant to train workers with a history of job mobility. Adopting a weighting approach to flexibly control for observed differences in the characteristics of risk-averse and risk-tolerant managers, we show that our findings cannot be explained by heterogeneity in either managers' observed characteristics or the type of firms where they work. All managers, irrespective of their risk preferences, are sensitive to the investment risk associated with training, avoiding training that is more costly or that targets those with less occupational expertise or nearing retirement. This provides suggestive evidence that 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).

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

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practices (e.g. performance pay, problem-solving teams, profit sharing, training, etc., see [Ichniowski et al., 1997](#); [Ichniowski and Shaw, 1999](#); [Black and Lynch, 2004](#)) 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 including firms' performance, financial and investment decisions, and exposure to systematic risk ([Bertrand and Schoar, 2003](#); [Schoar et al., 2023](#)). Moreover, managerial decision-making – as reflected in manager fixed effects – can be characterized by specific patterns consistent with the existence of heterogeneity in managerial “style” ([Bertrand and Schoar, 2003](#)) and corporate strategy, including preferences for internal growth and financial conservatism ([Schoar et al., 2023](#)). 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 incorrectly assigned leading to productivity losses.

We know less about the mechanisms through which managers influence organizational outcomes. Previous studies have traditionally “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. There is an emerging literature linking managerial skills to employee turnover ([Hoffman and Tadelis, 2021](#)), the effort workers provide ([Frederiksen et al., 2020](#)), task allocation ([Adhvaryu et al., 2022](#)), and the speed with which learning by doing occurs ([Adhvaryu et al., 2023](#)). Each provides a potential link between managerial decisions and firm productivity. Linking specific manager characteristics to organizational performance can be challenging using observational data, however, 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 is, after all, fundamentally about decision making under uncertainty, making managers' risk tolerance crucial for the decisions they make. Despite this, the consequences of managers' risk preferences have not been extensively studied. In a 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. Exceptions include recent studies demonstrating that managers' risk aversion is related to firms' financial policies and accounting procedures ([Graham et al., 2013](#); [Karpavičius and Yu, 2019](#); [Brown et al., 2023](#)). Moreover, [Brenner \(2015\)](#) shows that firm performance is negatively correlated with managers' risk-aversion. Using a laboratory experiment to investigate investment decisions in hypothetical research projects, [Carson et al. \(2022\)](#) show that more risk-tolerant decision makers are more likely to fund larger projects that potentially lead to larger returns. They conclude that managers' risk preferences might have an important impact on investments in potential breakthrough innovations and, consequently, on the profitability of firms.

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](#)). 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](#)).² At the same time, employers can be reluctant to engage in worker training (e.g. [Alfonsi et al., 2020](#); [Caicedo et al., 2022](#)) making it important to understand training investment decisions from the firm's perspective. As managers are typically the gateway to employees' opportunities for career development and progression ([McDowall and Saunders, 2010](#); [Fenizia, 2022](#); [Haegele, 2022](#)), 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 importance of skill development for strong, sustainable, and balanced growth ([International Labour Organization, 2011](#)) and the prevention of labour market exclusion ([OECD, 2018](#)).³

We begin by developing a stylized model linking managers' risk preferences to the profitability of firms' training investments. Managers' training decisions are modelled 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 workers are offered training is positively related to their 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 firm recoups its training investment.

¹ These 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 much of the lower productivity growth in Southern Europe is due to the inefficient management practices that limited the potential gains from the IT revolution that began in the mid 1990s.

² 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 generates 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.

³ For reviews of the work-related education and training literature see [Asplund \(2005\)](#), [Leuven \(2005\)](#), [Bassanini et al. \(2007\)](#), [Frazis and Loewenstein \(2007\)](#) and [Haelermans and Borghans \(2012\)](#).

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 next turn to using our data to provide evidence that risk affinity of managers is linked to a broad range of investment decisions that firms make including (but not limited to) those in workers. Specifically, we find that increases in manager risk affinity are associated with a significant increase in the probability that the firm has introduced new products, improved its products, adopted new production processes, or invested in new computers and machines. These results are broadly consistent with other findings that managers' willingness to take risks is associated with greater firm-level investments in digital technologies (Basiglio et al., 2023), safety (Sharma and Tarp, 2018), research and development (Abdel-Khalik, 2014), and riskier capital projects (Brown et al., 2023). Managers' tolerance for risk is also positively associated with both the incidence and intensity of training, particularly in tight labour markets.

Finally, we conduct an empirical investigation of the relationship between managers' risk preferences and investments in worker training. Our data come from a nationally representative, cross-sectional survey of German firms – the Cost-Benefit Survey – which is conducted every five years by the Federal Institute for Vocational Education and Training (BIBB) to elicit information about the costs and benefits of vocational training and recruitment. In the first step of our analysis, we provide evidence that managers' willingness to take risks is positively correlated with the likelihood that their firm invests in any worker training (extensive margin) as well as with the average amount invested per worker (intensive margin). Importantly, these relationships hold even after controlling for managers' time preferences. These first-stage results provide useful descriptive evidence consistent with the predictions of our theoretical model. At the same time, they are confounded by the non-random allocation of managers to firms, and indeed to jobs within firms, implying that they do not lend themselves to a causal interpretation.

Consequently, in a second step, we embed a discrete choice vignette study in the 2018 Cost-Benefit Survey. The vignettes involve fictitious training scenarios that are presented to survey respondents – primarily firm owners and human resource managers typically making such decisions on a daily basis – who are then asked which of two workers they would choose to train.⁴ 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. The experimental nature of our vignette design allows us to overcome the identification challenge that arises when the context in which training decisions are made is itself endogenous due to the selective matching of managers to firms, and to jobs within firms.

Using this experimental setting, we provide the first estimates of the impact of managers' risk preferences on their employment-related training decisions. When confronted with uncertainty about the returns to training, risk-tolerant and risk-averse decision makers have significantly different preferences over the workers they train. Importantly, risk aversion is associated with a heightened sensitivity to turnover risk. Risk-averse managers are less willing to train workers with a history of job mobility. Those who are risk-averse also reduce the probability of offering training around 30 percent more when this training is general. In contrast, all managers – irrespective of their risk preferences – avoid training that is more costly or that targets those with less occupational expertise or nearing retirement. This suggests that, from the perspective of managers, the risks of training are primarily linked 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).

While our vignette design overcomes many identification challenges through the experimental manipulation of training risks, we cannot exogenously vary managers' inherent attitudes towards those risks. Consequently, we investigate whether the differential responses of risk-averse and risk-tolerant managers is likely to be confounded by other factors related to risk preferences. We find no evidence that this is the case. Re-estimating our discrete choice models using flexibly constructed weights to equalize differences in the observed personal and firm characteristics of risk-averse and risk-tolerant decision makers demonstrates that not only do our main conclusions continue to hold, the disparity between risk-averse and risk-tolerant decision makers becomes even more pronounced. We conclude that our results are unlikely to be driven by the selection of risk-tolerant managers into firms which are investing more or differently in training.

Our conclusion that managers respond to the potential profitability of training when allocating training to workers opens the door for the alignment of training investments and training risks to be one mechanism through which managers influence firms' performances. As such, our research contributes to an emerging literature seeking to understand the ways that managers can enhance

⁴ 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. Vignette methods have also been used to study a variety of other labour 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).

worker, team, and firm productivity (see Hoffman and Tadelis, 2021; Frederiksen et al., 2020; Adhvaryu et al., 2022, 2023). We also extend the behavioural economics and management literature by demonstrating the importance of managers' risk preferences for the decisions they are willing to take. Finally, our vignette study design complements previous observational studies of the role of managerial style, strategy, and practice for organizational outcomes.

2. Theoretical framework

There is an extensive literature examining the circumstances in which firms provide – and pay for – training for their employees. Work-related training typically involves the development of some skills that may be specific to the current employer along with other more general skills that raise productivity both inside and outside the current firm.⁵ Becker (1962) was the first to highlight the crucial role that skill transferability plays in the allocation of training costs, arguing that, in perfectly competitive markets, firms have no incentive to pay for training that is completely transferable to other firms. Subsequent research demonstrates that this result breaks down, however, in the face of labour market rigidities, non-competitive market structures, and training that is both general and specific (see Acemoglu and Pischke, 1999a; Asplund, 2005; Frazis and Loewenstein, 2007, for reviews). Thus, in theory, a firm may pay for general training in a wide range of circumstances, including if: (i) it has monopsony or monopoly power (e.g. Stevens, 1994b; Acemoglu and Pischke, 1999a); (ii) matching and search frictions exist (e.g. Acemoglu, 1997; Acemoglu and Pischke, 1999b; Stevens, 1994a); (iii) information is asymmetric (e.g. Katz and Ziderman, 1990; Acemoglu and Pischke, 1998); (iv) general and specific training are complementary (e.g. Stevens, 1994b; Franz and Soskice, 1995; Acemoglu and Pischke, 1999a,b; Kessler and Lülfsmann, 2006); or (v) worker productivity depends on coworker skill levels (Booth and Zoega, 2000).⁶ In line with these model extensions, there exist a number of empirical studies providing evidence that employers pay at least partly for general training (Leuven and Oosterbeek, 1999; Booth and Bryan, 2007, see for example). At the same time, Hashimoto (1981) develops a model in which firms and workers share the costs and benefits of specific training as a form of long-term commitment device to prevent costly job separations.

Given our interest in the behaviour of individual managers, we abstract from the many factors driving training investments at the firm-level, and present a stylized principal-agent model that characterizes a manager's decision to train workers. The firms in which managers work 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:

$$V_i(H_j = 1|\theta_i) = pU(w_0 + B|\theta_i) + (1 - p)U(w_0 - D|\theta_i), \quad (1)$$

$$V_i(H_j = 0|\theta_i) = U(w_0|\theta_i). \quad (2)$$

Manager i offers 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

⁵ Lazear (2009) in fact argues that firm-specific training does not exist. Instead, he views all skills as general implying that it is only the skill mix and the weights attached to particular skills that are specific to each employer.

⁶ See Gersbach and Schmutzler (2012) for references on information asymmetries and complementarities.

long-term relationships and worker reciprocity (see Frazis et al., 2000; Leuven, 2005; Sauermann, 2023). 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. 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 employees who randomly miss out on training. At the same time, this retention effect is smaller for training that is portable and verifiable. Managers thus face more turnover risk when making general training investments than when making specific training investments, everything else equal.⁷

3. Data and descriptive evidence on training incidence in firms

3.1. Data

In our empirical analysis, we use data from two waves of the *Cost-Benefit Survey* by the Federal Institute for Vocational Education and Training (BIBB). These repeated cross-sectional firm-level-surveys are conducted every five years and aim to elicit the costs and benefits of vocational training and recruitment within German firms. For the analysis in this paper, we use the two latest waves of 2013 and 2018 (see Schönfeld et al., 2016, 2020). For each of the surveys, responding firms addresses are drawn from the Federal Employment Agency (*Bundesagentur für Arbeit*) administrative register, including all firms with at least one employee subject to social security contributions. Thus, our samples are 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.⁸ The interviews take place in the firm using the computer-assisted personal interviewing (CAPI) method and last between 50 and 80 min, depending on a firm's involvement in training and recruitment activities. For the wave 2018, the data source of our vignette experiment, the data was gathered by *infas* (*Institut für angewandte Sozialwissenschaft*) between June 2018 and July 2019. The following measures are available in the data.

Training information With respect to worker training, we can draw on different measures in the data. First, the training participation variable is a dummy, which indicates whether the firm has fully or partly financed continuing training courses for their employees in the respective calendar year. Second, for those firms who offer training, we also observe the number of trained workers and the training investment per trained worker (in Euro). Concerning training investment, the survey gathers information on both direct training costs (i.e. fees and travelling expenses) and indirect training costs, such as forgone productivity due to the absence from the work place.

Risk measurement There are alternative approaches to measuring people's risk preferences. In experimental studies, participants are often asked to make repeated choices between alternative lotteries involving a financial payoff (e.g. Holt and Laury, 2002; Eckel and Grossman, 2002; Crosetto and Filippin, 2013). Randomly choosing one or more lotteries for actual payment ensures that these questions are incentive-compatible, i.e. that respondents reveal their true attitudes towards risk. Lottery questions can be conceptually difficult, however, resulting in some participants making inconsistent choices (Dave et al., 2010) and, potentially, being dropped from the analysis. More importantly, incentivized lottery questions are infeasible in large-scale studies. Instead, self-reported measures of risk preferences are typically incorporated into large surveys (e.g. Barsky et al., 1997; Donkers et al., 2001; Dohmen et al., 2011).

Our risk measure comes from respondents' self-reported general willingness to take risks. Specifically, respondents answer 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?" using an 11-point Likert scale that ranges from "not at all willing to take risks" to "very willing to take risks". This general risk question has been validated in an incentivized experiment by Dohmen et al. (2011). People's responses are predictive of behaviour across numerous domains, providing evidence that they capture a stable, underlying trait.

Control variables We have a multitude of structural firm variables (such as firm size, economic sector, region, and legal status of the firm) that we can use as control variables in our later regressions. Furthermore, we can additionally control for firm-level institutions potentially related to training decisions (works council, collective bargaining agreement, and involvement in apprenticeships). Finally, we control for the decision makers' position in the firm and their degree of decision-making power.

⁷ 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 labour 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).

⁸ Regarding the selection of the interview partners, the interviewers first contact the firm (via postal letter) and ask for a contact person most knowledgeable regarding firms' decision making on training and recruitment. The interviewer then arranges a date for the personal interview with that contact person in the firm.

3.2. Training incidence in German firms

Estimation sample We begin by investigating the correlation between managers' risk preferences and firms' training investments. Extending the work of Jansen et al. (2017) who examine this relationship in the 2013 *Cost-Benefit Survey*, we utilize data from both 2013 and 2018. In 2013, our initial sample includes 3940 firms. Dropping all cases with missing values for either our training measures or individual-level characteristics, we obtain a working sample of 3042 firms. Similarly, in 2018, we have an estimation sample of 3323 firm, derived from a total of 4045 firms in the initial sample. Pooling both waves to allow for a joint analysis results in an estimation sample of 6364 cases. Not all firms are selected for the vignette study. Consequently, we also provide estimates of the correlation between manager risk preferences and firm training investments in the sample of vignette firms providing training information. The selection of firms into the vignette study is described in Section 4.⁹

Training measures, risk preferences, and controls Key descriptive statistics are shown in Table 1. About 70 percent of firms provide training in 2013, spending on average 968 Euros per trained worker. In 2018, the share of firms offering training is somewhat higher (75 percent). Concerning the distribution of our risk measure, we find that risk affinity (on a scale from 0 to 10) increased slightly from 5.1 in 2013 to an average of 5.5 in 2018.¹⁰ Furthermore, we observe moderate differences in the distribution of decision maker positions of the respondents. For example, while the share of firm owners in the sample of 2013 is somewhat larger than in the sample of 2018, we observe the opposite for the share of human resources managers. With respect to the firm level institutions of works council presence and apprenticeship training, we find only small differences. The coverage by collective agreements, however, is lower in 2018 than in 2013, which is in line with the findings of other firm-level surveys (Ellguth and Kohaut, 2021). Finally, we find only marginal differences in the distribution of the firms size, employee occupation, economic sector, or region.¹¹

The distribution of risk tolerance in our sample of decision makers (pooled sample) is shown in Fig. A.1A in the Appendix. The mean risk preference is 5.32 (median = 5) 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 Fig. A.1C). The risk tolerance of our sample is, in fact, more similar to SOEP respondents in high-status occupations (see Fig. A.1D).¹² 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 both a continuous measure of decision makers' risk preferences as well as a binary indicator that differentiates relatively risk-tolerant (i.e. > median) from risk-averse ($\leq$ median) decision makers.

Descriptive statistics are reported separately for firms with a relatively risk-tolerant vs. relatively risk-averse manager in Appendix Table A.2. Firms with more risk-tolerant decision makers are more likely to be export-oriented and face high competition; they are less likely to be a foundation, institution, or authority. We do not observe any major differences across managers' risk tolerance in other firm characteristics, including firm size, having a works council, collective bargaining coverage, or whether or not the firms train apprentices. We do observe some differences in the sectoral distributions, the position the interviewed manager holds within the firm, and the decision power she/he has.

Manager risk preferences and firm investments Before considering the relationship between manager risk preferences and firm training investments, we begin our analysis by providing descriptive evidence that the risk tolerance of managers is associated with a broad range of firm investments (see Table A.3 in the Appendix). Specifically, we find that a one standard deviation increase in managers' risk affinity is associated with a significant increase in the probability that the firm has introduced new products (4.2 percentage points), improved its products (5.3 percentage points), adopted new production processes (2.8 percentage points), or invested in new computers and machines (4.9 percentage points). These results are consistent with previous research findings that greater firm-level investments in digital technologies (Basiglio et al., 2023), safety (Sharma and Tarp, 2018), research and development (Abdel-Khalik, 2014), and riskier capital projects (Brown et al., 2023) are all linked to managers' risk affinity.

We next run a series of regressions that estimate the association between managers' risk tolerance and the investments in worker training that firms make. Due to the regional stratification of our survey, we use design weights (i.e. the inverse of a firm's sampling probability) in these regressions. Results are provided in Table 2.¹³ Column (1) focuses on the intensive margin by investigating the log of training investment per worker (in Euro). The respective coefficient is positive and significant, indicating a 20.7 percent increase in training investments in case of a one standard deviation increase in managers' risk affinity. This relationship holds even after controlling for managers' time preferences and the self-reported tendency to procrastinate (see column (2) of Table A.5 in the Appendix).¹⁴ Column (2) provides an estimate for the extensive margin using the pooled sample from 2013 and 2018. The results

⁹ Note that the sample size deviates slightly from the sample size of the vignette analysis, because some vignette firms did not respond to questions about training provision.

¹⁰ Table A.1 in the Appendix shows, that there is quite a bit of heterogeneity both in training incidence and risk affinity across sectors. For example, the share of training firms ranges from 0.48 (Agriculture/Mining) to 0.95 (Public Administration). At the same time, risk affinity varies between 4.46 (Energy Supply) and 5.93 (Accommodation Activities).

¹¹ The description of the latter variables is not shown in detail but is available upon request.

¹² And the same is true for our vignette participants, which we will describe in more detail in Section 4, as can be seen from Fig. A.1B.

¹³ Table A.4 in the Appendix shows that the results are qualitatively very similar if we do not use weights.

¹⁴ The 2013 survey included questions asking about the preference for future profits and the tendency to delay action (procrastination). The respective questions were: "With regards to financial decisions, how willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?" and "To which degree does the following statement apply to you? I tend to postpone things even though it would be better to get them done right away". Unfortunately, these questions have only been asked in 2013 and not in 2018, such that we can only replicate column (1) of Table 2. The estimated coefficient for risk aversion is qualitatively stable and statistically significant when additionally controlling for time preferences and procrastination.

Table 1
Selected summary statistics.
Source: BIBB-CBS 2013/2018, own calculations.

	Wave			
	2013	2018	2013/2018	2018 vignette firms
	(1)	(2)	(3)	(4)
Training information:				
Training costs per trained worker (in Euro)	968			
Std. Dev.	1613			
Firm provides worker training (yes/no)	0.69	0.75	0.72	0.76
Std. Dev.	0.46	0.43	0.45	0.42
Risk measurement:				
Risk-affinity (Scale 0–10)	5.10	5.53	5.32	5.46
Std. dev.	2.39	2.11	2.25	2.14
Risk-high ^a	0.42	0.36	0.47	0.36
Managers' characteristics:				
Male		0.57		0.57
Educational status:				
No vocational training		0.01		0.01
Vocational training		0.19		0.20
Advanced vocational degree		0.37		0.35
Academic degree		0.43		0.44
Firm tenure (in Years)		14.62		14.44
Std. dev.		10.78		10.47
Firm position:				
Owner	0.42	0.35	0.39	0.36
CEO	0.16	0.13	0.14	0.13
Department head	0.1	0.09	0.09	0.07
Head HR	0.11	0.16	0.14	0.17
Head commerce	0.05	0.08	0.06	0.09
Head of training	0.08	0.08	0.08	0.07
Other position	0.09	0.11	0.10	0.11
Manager gross wage (in Euro)	3834	4378	4118	4434
Std. dev.	1897	1883	1909	2002
Firm characteristics:				
Legal status of firm:				
Autonomous individual holding	0.65	0.61	0.63	0.63
Independent operation as part of enterprise	0.11	0.13	0.12	0.11
Corporate headquarter	0.05	0.06	0.05	0.07
Branch office	0.10	0.10	0.10	0.09
Foundation, institution, authority	0.05	0.05	0.05	0.05
Something different	0.04	0.04	0.04	0.05
Firm-level institutions:				
Work council	0.23	0.23	0.23	0.23
Collective bargaining coverage	0.47	0.41	0.44	0.41
Firm trains apprentices	0.78	0.75	0.76	0.72
Number of employees:				
Number of employees: 1–9	0.34	0.30	0.32	0.29
Number of employees: 10–49	0.38	0.39	0.39	0.40
Number of employees: 50–499	0.23	0.24	0.24	0.26
Number of employees: ≥500	0.05	0.05	0.05	0.05
Export oriented ^b	0.11	0.11	0.11	0.11
High competition ^b	0.72	0.66	0.69	0.68
Observations	3042	3322	6364	1070

Note: The table shows descriptive statistics for wave 2013 (column 1), wave 2018 (column 2), the pooled sample of wave 2013 and 2018 (column 3) and firms that took part in the vignette in 2018 (column 4). All numbers are shares unless stated otherwise.

^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, and a value of 0 otherwise.

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

suggest that risk affinity is positively correlated with a firm's likelihood of providing training to their workers.¹⁵ A one standard deviation increase in risk affinity is associated with a significant increase of 2.0 percentage points in the likelihood to provide worker training.

Finally, from a firm's perspective, the riskiness of its training investments depends, at least in part, on the likelihood that trained workers will receive outside offers from other firms and end their current employment before the firm's training costs have been

¹⁵ Column (1) replicates the results for the intensive margin reported in Jansen et al. (2017).

Table 2

Regression models (Weighted): Training decision (and investment) of firms and risk preference of decision maker.

Source: BIBB-CBS 2013/2018, own calculations.

	Per-head investment	Training yes/no	
	Wave 2013	Wave 2013 and 2018 pooled	Wave 2018 vignette firms
	(1)	(2)	(3)
Risk affinity (std)	0.207*** (0.078)	0.020** (0.008)	0.024* (0.013)
Constant	1.892** (0.910)	−107.040*** (25.716)	1.402 (0.977)
Controls	Yes	Yes	Yes
Observations	3042	6364	1023

Note: The table displays marginal effects from linear (column 1) and probit regressions (columns 2/3) with standard errors in parentheses. In column (1) the dependent variable is the log of training investment per worker (in Euro). In column (2) and (3) the dependent variable is a dummy indicating whether a firm provides training to their workers. The main explanatory variable of interest is the managers' standardized self-reported risk affinity measured using an 11-point Likert scale. Controls include the respondents' decision power (4 categories), position in firm (7), manager wage (in Euro), the firms' legal status (6), work council (yes/no), collective bargaining (yes/no), training apprentices (yes/no), firm size (4), occupation of worker (2-digit KldB: 35), industry (1-digit NACE: 18), region (16), and wave (2013/2018). Design weights account for the regional stratification of our survey.

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

recovered. For this reasons, tight labour markets are likely to make manager risk preferences even more salient for firms' investment decisions. We explore heterogeneity in the relationship between manager risk preferences and firm training investments using survey information about (i) the competition that firms face and (ii) the tightness of the local labour market.¹⁶ On average 65 percent of firms face high competitive pressure; this ranges from 12 percent in Public Administration to 86 percent in Finance and Insurance (see Table A.1). At the same time, firms rate the tightness of the labour market rather low with an average of 3.85. We split the sample at the median of both variables and re-estimate the main specification from Table 2. We find that the association between risk tolerance and training investments is higher (2.4 percentage points) for firms that face a tight labour market; whereas we do not see differences with respect to the competitive situation in their product market (see Table A.6).

Taken together, these results support the view that manager risk preferences are associated with a range of firm investment decisions.

4. Vignette design

Overall, the regressions in Section 3.2 demonstrated that there is a positive correlation between managers' risk affinity and the incidence of training in the firms where they are employed. The distribution of managers across firms is not random, however, and this positive correlation might, for example, reflect the sorting of risk-tolerant managers into firms that tend to invest more in worker training. Consequently, we embed a vignette experiment in the 2018 wave of the survey. Of the 4045 firms interviewed in 2018, approximately one third (1358) were randomly selected to take part in the vignette experiment.¹⁷ After excluding respondents who were not willing to participate in the vignette experiment as well as those from firms with multiple representatives participating in the survey, we are left with a sample of 1161 firm representatives (≈ 85 percent). Respondents are confronted with the vignette experiment after having answered several batteries of questions focusing on the vocational training of employees and before providing personal information about themselves (e.g. personality traits, risk preferences, experience, etc.).¹⁸ Information about managers' personality traits and economic preferences is a key advantage of our data. 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.

¹⁶ This information comes from two questions. In the first question, firms are asked whether they are under high competitive pressure in their market, and they can answer with yes or no. In the second question, they are asked how they would consider the availability (quantity) and fit (quality) of workers in the labour market. They respond on a scale from 1 (low) to 5 (high).

¹⁷ We have tested whether randomization was successful by running a regression of the dummy of being assigned to the vignette on all available individual and firm characteristics. Only three (out of 68) variables are statistically significant and based on a joint test we cannot reject the hypothesis that all estimated coefficients are zero (Likelihood-Ratio χ^2 -test on joint significance; $\chi^2(68)$: 62.42; p -value: 0.6681), confirming that randomization was successful. Detailed results are available on request.

¹⁸ We align the sample and the target population by surveying and selecting those firm representatives that have decision-making power. This is an important step in ensuring the external validity of our discrete choice experiment (see Hainmueller et al., 2015, for details).

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 expertise and job 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

The skilled worker ...

... is female.

... is 45 years old.

... has above average occupational expertise.

... 1 time changed employer within the last 5 years.

The training ...

... is completely usable also in other firms.

... takes 5 working days.

... is covered by 100% of the employer. The participant has no costs.

☐

Profil Skilled worker 2

The skilled worker ...

... is male.

... is 55 years old.

... has average occupational expertise.

... never changed employer within the last 5 years.

The training ...

... is partly usable also in other firms.

... takes 2 working days.

... is not covered by the employer. 100% of costs are taken over by the participant.

Fig. 1. Vignette example. Note: The figure displays an example of the choice set-up that is presented to each respondent, who has to decide between two different 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). The training scenario is characterized by three attributes (transferability, duration, and cost sharing agreement). Each respondent is confronted with six of such decisions between two alternative worker/training combinations, each characterized by seven attributes in total. An overview of all attributes and attribute values is provided in Table A.7.

Vignette design In the vignette experiment, each respondent is 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.¹⁹ To be more specific, 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 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.7, while Fig. 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. The total number of possible vignettes therefore amounts to 1944 ($2 \times 4 \times 3 \times 3 \times 3 \times 3 \times 3$).

Having defined the attributes and attribute values for our vignette study, we move on to the actual implementation of the vignette experiment in the survey. The total number of possible choice sets in a *full factorial design* exceeds 1.8 million.²⁰ 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).²¹

Our aim is to reduce the number of choice sets to a feasible set of choices to be presented to our respondents. Thereby, the general aim is to estimate our β (i.e. the respondents' preference for attributes in the experiment – see Section 5) as precise as possible. The precision of the estimates is determined by the variance–covariance matrix of the estimated coefficients. An efficient vignette design minimizes the size of the variance–covariance matrix and thereby the *D*-error. Given that the inverse of the *D*-error is the *D*-efficiency, we can apply the *Stata* command *dcreate* (Hole, 2015a) to our setting of attributes and attribute values to maximize the *D*-efficiency of our design.²² This is put into practice in two steps. First, *dcreate* reduces the number of different alternatives. In our case, the command creates 216 (i.e. 108 choice sets). Second, the command groups 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 fully randomized as is the order of choice sets within any block.

Table 3 provides descriptive evidence that our vignette experiment fulfils two important properties of an efficient choice designs, i.e. level balance and minimal overlap (Huber and Zwerina, 1996). Concerning the former, column (1) shows that the frequency

¹⁹ 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.

²⁰ The full matrix of possible attribute combinations has 1944 rows, which yields $(1944 \times 1943)/2 = 1,888,596$ possible choice sets of applicants.

²¹ Huber and Zwerina (1996) propose four properties for efficient choice designs: (1) orthogonality, (2) level balance, (3) minimal overlap, and (4) utility balance.

²² *dcreate* uses a modified Fedorov algorithm (Huber and Zwerina, 1996; Carlsson and Martinsson, 2003) to generate sets of vignettes (candidates).

Table 3
Proportional frequencies and choices made.
Source: BIBB-CBS 2018, own calculations.

Attributes	Mean	
	Alternatives (1)	Decisions (2)
Training candidate:		
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	6339

Note: The table shows the frequency of attribute values in the vignette study in column (1) and the frequency of attribute values of chosen candidates in column (2).

of attribute values is equalized across the two choices, which is in line with the level balance property. Concerning the latter, our design is consistent with the minimal overlap property because 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 3. 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.

Vignette estimation sample We restrict our sample to participants who answer the question on risk tolerance. This leaves us with an estimation sample of 1070 decision makers, for whom we observe 6339 training decisions involving 12,678 choice alternatives which we use to assess the link between decision makers' risk preferences and their training choices.²³ 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 ($\leq$ median) decision makers. Approximately 64.1 percent (4065 out of 6339) of the total training choices are made by risk-averse decision makers, whereas 35.9 percent (2274 out of 6339) of the decisions are made by relatively risk-tolerant decision makers. Similar to the pooled sample, we find for this sub-sample a positive correlation between managers' willingness to take risk and training incidence at the firm level, reported in column (3) in Table 2.²⁴

Column (4) in Table 1 shows that our vignette participants are predominantly men (57 percent). 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

²³ For 96 percent of the sample we observe six choices, for 4 percent we observe less. Results are robust if we drop those who do not make all of the training decisions presented to them.

²⁴ In our vignette sample from 2018, we also observe the locus of control and the Big Five of the managers. When we regress an indicator for whether the firm invested in training on our measures of risk aversion and different personality traits, we find that the effect of risk aversion is rather stable after the inclusion of these personality traits, but estimates become less precise and have an associated p -value of 0.18 (see column (4) of Table A.5 in the Appendix). Moreover, the size of the coefficient is smaller when we compare it, for example, to the coefficients of our measures of conscientiousness and agreeableness. The role of other manager characteristics for training and investment decisions is an important topic for future research.

(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.

5. Empirical strategy and results

In our theoretical framework, decision makers choose whether to train or not to train a worker. A worker receives 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). Specifically, 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 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.

5.1. 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 . We assume that participants maximize their utility. Thus, given choice set t , decision maker i chooses alternative k if

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

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} :

$$U_{ijt} = \beta_i' x_{ijt} + \epsilon_{ijt}, \quad (3)$$

where β_i is an individual-specific coefficient vector capturing heterogeneity in preferences for various training options and ϵ_{ijt} is an error term that is assumed to be independent and identically distributed. The coefficient vector can be decomposed as $\beta_i = \bar{\beta} + v_i$, where $\bar{\beta}$ denotes the population mean and v_i captures unobserved individual-specific deviations from the population average. The error term ϵ_{ijt} can be interpreted as a mistake the individuals make when they compute and compare the utilities of the different choice alternatives.

Our specification has the advantage of allowing decision makers to have different (unobserved) preferences over the attributes of choice alternatives. Heterogeneity in preferences is accounted for through v_i . We assume that v_i is uncorrelated with the observed attributes of choice alternatives x_{ijt} and model it as a random effect. This maintained independence assumption is 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 error terms ϵ_{ijt} follow an extreme value distribution. This results in a mixed logit model. The individual likelihood contribution L_i conditional on the random effects v_i is described by:

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

where d_{i1t} is a dummy variable 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:

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

Since the integral in Eq. (4) cannot be calculated analytically, we cannot estimate the model with exact maximum likelihood. Instead, we estimate the parameters of the continuous mixing distribution using maximum simulated likelihood (MSL), whereby the

integrals are approximated through simulation (see [Revelt and Train, 1998](#); [Train, 2009](#)). The simulations are based on R draws from the distribution $f(\beta)$. The MSL estimator is biased due to the logarithmic transformation of the probabilities. This bias decreases with the variance of the simulated probabilities, and therefore the bias decreases as the number of draws R increases ([Bhat, 2001](#)). This implies that we usually need a large number of draws to achieve a small bias, and this often goes along with (very) long run times for the MSL estimation. There exist different procedures for improving the approximation of the integrals by taking systematic instead of random draws from the distribution. In our application we employ Halton draws to reduce the simulation variance, which have been shown to work well for mixed logit models (see [Train, 1999](#); [Bhat, 2001](#); [Haan and Uhlenborff, 2006](#)). Standard Halton sequences tend to be highly correlated for higher-dimensional integrals. [Bhat \(2003\)](#) demonstrates that scrambled Halton sequences perform better than standard Halton sequences for models with higher-dimensional integrals. [Kolenikov \(2012\)](#) discusses several methods for scrambling Halton sequences, including square-root scrambler, random multiplier scrambler, and Atanassov's modified Halton sequence. We scramble the Halton sequence using the square-root scrambling method.²⁵

5.2. Model selection

We consider model selection by estimating a series of models with alternative approaches to account for (i) unobserved heterogeneity in preferences; and (ii) training costs. Our results are presented in [Table 4](#).

We begin by comparing standard (conditional) logit estimates that do not account for unobserved heterogeneity in preferences (column 1) with mixed logit estimates that do.²⁶ Specifically, we estimate 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 random coefficients follow a multivariate normal distribution.

The magnitude of the estimated mean coefficients changes across the different models. They are larger in the two mixed logit models compared to 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). The reason behind this outcome is that the mixed logit model decomposes the unobserved part of utility into $v'_{ij}x_{ij} + \epsilon_{ijt}$, and the mean coefficients are normalized based on the variance of the error terms ϵ_{ijt} . While the error term ϵ_{ijt} in a standard logit model captures any variance in the parameters, the variance in the error term captures less of this variance the more flexibly we specify the distribution of the random effects. In other words, the (correlated) random effects explain a large part of the variance in the choice patterns. This leads – due to the normalization based on the variance of ϵ_{ijt} – to an increase in the magnitudes of the mean coefficients when we move from column (1) to column (3) in [Table 4](#) (for similar results see [Revelt and Train, 1998](#); [Eriksson and Kristensen, 2014](#)).²⁷

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 analysing 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 4](#). 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. This

²⁵ We estimate the mixed logit models with Stata using the routines by [Hole \(2007\)](#).

²⁶ The marginal effects of the standard conditional logit model are comparable to the estimated parameters resulting from an OLS regression. For linear models, we have to construct for each choice set t the difference in the observed characteristics for options $j = 1$ and $j = 2$, and then regress a dummy indicating whether or not the individual i chooses option $j = 1$ on these differences in observed characteristics. The advantage of the logit model is that we can link the coefficient estimates to an underlying utility. Moreover, we can easily introduce (correlated) unobserved heterogeneity within a mixed logit model.

²⁷ Comparing columns (1) and (2), the size of the relative change in the coefficients besides that for gender – which is only statistically significant at the 10% level – is relatively similar across the different coefficients and lies between 29 percent and 42 percent. When we compare columns (1) and (3), we observe larger changes and also a larger heterogeneity in the relative changes, ranging from 70 percent to 143 percent. This larger heterogeneity is linked to the more complex structure of the distribution of the parameters in the model with correlated random effects, which affects the estimates of the coefficients differently.

Table 4

Parameter estimates for logit and mixed logit models.

Source: BIBB-CBS 2018, own calculations.

	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** (0.029)	0.076* (0.038)	0.092* (0.052)	0.061* (0.038)	0.064* (0.038)
Age					
25 years old	0.640*** (0.052)	0.842*** (0.072)	1.240*** (0.118)	0.856*** (0.070)	0.860*** (0.070)
35 years old	0.598*** (0.051)	0.805*** (0.071)	1.172*** (0.116)	0.822*** (0.071)	0.823*** (0.071)
45 years old	0.499*** (0.050)	0.654*** (0.068)	0.918*** (0.103)	0.655*** (0.066)	0.659*** (0.066)
55 years old	Ref.				
Occupational expertise					
Above average	0.665*** (0.051)	0.927*** (0.072)	1.335*** (0.125)	0.914*** (0.069)	0.922*** (0.069)
Average	0.389*** (0.042)	0.502*** (0.052)	0.783*** (0.093)	0.491*** (0.051)	0.493*** (0.051)
Below average	Ref.				
Job mobility	−0.351*** (0.021)	−0.487*** (0.033)	−0.687*** (0.055)	−0.481*** (0.032)	−0.482*** (0.032)
Training context:					
Usability in other firms					
Completely usable	−0.413*** (0.041)	−0.558*** (0.055)	−0.763*** (0.084)	−0.554*** (0.053)	−0.552*** (0.053)
Partly	−0.316*** (0.039)	−0.448*** (0.053)	−0.648*** (0.081)	−0.436*** (0.051)	−0.436*** (0.052)
Only usable in firm	Ref.				
Cost coverage by the employer					
100 percent	−0.135*** (0.038)	−0.190*** (0.050)	−0.329*** (0.073)		
50 percent	0.012 (0.040)	0.026 (0.051)	0.023 (0.076)		
0 percent	Ref.				
Training duration	−0.038*** (0.005)	−0.054*** (0.007)	−0.068*** (0.011)	−0.034*** (0.008)	−0.035*** (0.008)
Direct costs (for employer)				−0.149*** (0.035)	−0.149*** (0.036)
SD:					
Female		0.411*** (0.091)	0.466*** (0.117)	0.420*** (0.088)	0.427*** (0.087)
Age					
25 years old		0.530*** (0.145)	1.245*** (0.189)	−0.452*** (0.161)	−0.493*** (0.151)
35 years old		0.499*** (0.144)	1.233*** (0.187)	0.507*** (0.145)	0.506*** (0.148)
45 years old		−0.320 (0.205)	1.170*** (0.204)	−0.309 (0.205)	−0.288 (0.213)
Occupational expertise					
Above average		1.174*** (0.089)	2.370*** (0.188)	1.152*** (0.086)	1.163*** (0.087)
Average		−0.078 (0.183)	1.318*** (0.139)	−0.004 (0.172)	0.005 (0.178)
Job mobility		0.362*** (0.058)	0.489*** (0.079)	0.356*** (0.057)	0.369*** (0.055)
Usability in other firms					
Completely		−0.288 (0.155)	0.964*** (0.155)	0.305 (0.162)	0.255 (0.188)
Partly		−0.151 (0.173)	0.931*** (0.138)	0.100 (0.213)	0.073 (0.228)

(continued on next page)

drop is linked to the fact that the direct costs are a function of the training duration. While the coefficient in column (2) captures the costs linked to the absence of the worker and the direct training costs, the coefficient in column (4) only captures the costs

Table 4 (continued).

Cost coverage by the employer					
100 percent		0.033 (0.211)	0.804*** (0.151)		
50 percent		−0.195 (0.249)	0.817*** (0.146)		
Training duration		0.097*** (0.014)	0.132*** (0.019)	0.094*** (0.013)	0.096*** (0.013)
Direct costs (for employer)				0.022 (0.158)	0.037 (0.196)
Observations	12,678	12,678	12,678	12,678	12,678
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: The table displays means and standard deviations (SD) based on logit models with their corresponding standard errors in parentheses. The estimation is based on 300 scrambled Halton draws. The dependent variable indicates whether a candidate was picked or not. Column (1) displays (conditional) logit estimated that do not account for unobserved heterogeneity. Column (2) is a mixed restricted logit model with uncorrelated random coefficients. Column (3) show the results from the correlated mixed logit model that is estimated using an unrestricted variance–covariance matrix for random parameters. Both Column (2) and (3) assume that the unobserved heterogeneity follows a multivariate normal distribution. Column (4) and (5) are specified like column (2) but include direct training costs rather than the cost sharing rule.

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

linked to the absence of the worker due to the training participation. Estimates for the other attributes of the choice alternative are very similar to those reported in column (2). Finally, the assumption that the random coefficients in our mixed logit models follow 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.

5.3. Results

5.3.1. 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 4 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 5.²⁸

Decision makers are slightly more likely (1 percentage point) to offer training to female candidates than to their male counterparts. The absence of a negative gender gap in training offers is interesting given that managers evaluations of applications in the hiring process for apprenticeships – a specific type of entry-level position – appear to be gender biased (Kübler et al., 2018). 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). One potential explanation for this finding is that, rather than strictly favouring 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.

²⁸ The calculation of the marginal effects is based on the 6339 choice sets in our vignette study.

Table 5
Marginal effects and willingness-to-pay (in Euro).
Source: BIBB-CBS 2018, own calculations.

	Marginal effects	Willingness-to-pay (in Euro)	
	Mixed logit Direct costs (1)	Pref. space (2)	WTP- space (3)
Training candidate:			
Female	0.0085 (0.057)	416.17 (278.08)	452.79 (286.98)
Age			
25 years old	0.1335** (0.063)	5797.54*** (1400.71)	5880.33*** (1452.69)
35 years old	0.1275* (0.066)	5553.43*** (1337.66)	5631.44*** (1381.06)
45 years old	0.1050*** (0.040)	4433.84*** (1117.47)	4543.92*** (1169.79)
Occupational expertise			
Average	0.0860*** (0.006)	3306.67*** (844.44)	3579.00*** (948.25)
Above average	0.1311 (0.141)	6199.69*** (1501.69)	6465.08*** (1606.13)
Job mobility	−0.0641 (0.039)	−3252.46*** (778.43)	−3334.07*** (815.41)
Training context:			
Usability in other firms			
Partly	−0.0718*** (0.012)	−2937.83*** (768.17)	−2939.08*** (784.72)
Completely	−0.0911** (0.036)	−3710.20*** (940.96)	−3814.00*** (986.27)
Training duration	−0.0176 (0.012)	−232.80** (97.07)	−235.23** (100.06)
Direct costs (for employer)	−0.0188* (0.011)		
Observations	12,678	12,678	12,678

Note: Column (1) shows the average marginal effects corresponding to the mixed logit model with direct costs (see column (4) in Table 4). Columns (2) and (3) display the willingness-to-pay (in Euro) based on a fixed direct cost coefficient and an estimation in the WTP-Space.

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

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 €1000 has a similar effect in reducing the likelihood that training is offered.

5.3.2. 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. In general, an individual's willingness-to-pay for an observed characteristic corresponds to the change in the price that keeps the individual's utility constant given a change in the attribute. In our model, for decision maker i , the average willingness-to-pay for attribute x_{it} across all choice sets t corresponds to the ratio of the coefficient of this attribute β_{it} 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. In other words, we can interpret the willingness-to-pay measures only in terms of managers' utility – measured in monetary terms – if there is a direct link between the firm profits and the income of the manager. If this underlying assumption is not fulfilled, we can more generally interpret these measures in terms of the willingness of managers to spend part of their budget for specific characteristics of the training options.

We use two approaches to estimate willingness-to-pay parameters. In the first approach, we adopt the standard method 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. This approach is called *estimation in preference space*. We proceed in two steps. In the first step, we use our model of decision maker preferences (see Eq. (3)) including direct costs as a linear term. Compared to the specification reported in column (4) of Table 4, we estimate the model with a constant cost coefficient, i.e., the cost coefficient is assumed to be the same for all individuals. This restriction is in line with the results from the more flexible model, which suggests a small and insignificant variance in the cost parameter. In the second step, we divide the estimated mean coefficient for a specific characteristic by the estimated cost parameter. This ratio gives us an estimate of the willingness-to-pay.

Previous literature has pointed out that the estimation in preference space with a fixed price coefficient can be too restrictive, while a model allowing for a random price coefficient can result in highly skewed distributions with unrealistic means and standard deviations (Train and Weeks, 2005; Hole and Kolstad, 2012). Our second approach, the *estimation in willingness-to-pay space*, circumvents these issues. This approach is based on reformulating the model such that estimated coefficients directly represent willingness-to-pay measures, and these coefficients are allowed to vary across individuals following a multivariate normal distribution. More concretely, instead of estimating the parameters of $U_{ijt} = \beta'_i z_{ijt} + \beta_{ip} c_{jt} + \epsilon_{ijt}$, we estimate the parameters of $U_{ijt} = \beta_{ip} [\gamma_i z_{ijt} + c_{jt}] + \epsilon_{ijt}$, with $\gamma_i = \beta_i / \beta_{ip}$. c_{jt} are the direct program costs and z_{ijt} contains other individual and program specific characteristics, with $x_{ijt} = [z_{ijt} \ c_{jt}]$. This approach can produce different results than the estimation in preference space (see Train and Weeks, 2005; Hole and Kolstad, 2012, for a comparison of methods). Column (4) of Table 5 shows the mean results for willingness-to-pay in preference space, while column (5) refers to the results in willingness-to-pay space.²⁹ 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 (€5800) and workers with above average occupational expertise ($\sim$ €6200) 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 sizeable (€-3700). 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 €3250.

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.

5.3.3. 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. Although we are able to exogenously vary the riskiness of training, which overcomes the bias associated with the endogenous matching of managers to firms and to jobs within firms (Bertrand and Schoar, 2003; Hoffman and Tadelis, 2021, see), estimating the causal impact of risk preferences would also require exogenous variation in people's attitudes towards risk which we do not have. Instead, we conduct a heterogeneity analysis by re-estimating our models using specifications that allow the observed attributes of choice alternatives to be fully interacted with our standardized, continuous measure of decision makers' risk aversion. The complexity of our estimation model makes simultaneously accounting for multiple observed decision maker characteristics intractable. To the extent that risk preferences are correlated with other relevant characteristics, e.g. time preferences, our estimates will be confounded. We account for this by constructing weights to equalize the differences in the observed personal and firm characteristics of risk-averse and risk-tolerant managers.

Results are reported in Table 6. 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.³⁰

The baseline model in Eq. (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 Tables 4 and 6. We find that, overall, decision makers with different levels of risk preferences do indeed have different preferences for the observed attributes of training alternatives.³¹ 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 workers who are female, older, and have more occupational experience.³² 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.

²⁹ The estimations in the willingness-to-pay space are performed with the Stata command *mixlogitwp* (Hole, 2015b).

³⁰ 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.

³¹ The test-statistic is 23.1 with 12 degrees of freedom, which corresponds to a *p*-value of 0.017.

³² This also holds in a specification with correlated random effects.

Table 6
Parameter estimates for mixed logit model with interaction.
Source: BIBB-CBS 2018, own calculations.

	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)

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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 6, 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.9 in the Appendix). Moreover, we find strong evidence for heterogeneous preferences regarding the transferability of the human capital created during training. Risk-tolerant decision

Table 6 (continued).

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)
Occupational expertise	
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	−3793
Number of draws	300
LR test statistic	23.11
p-value	0.017

Note: The table displays means and standard deviations (SD) based on a mixed logit model that allows the observed attributes of choice alternatives to be fully interacted with the standardized, continuous measure of decision makers' risk aversion. Direct training costs are controlled for. The dependent variable indicates whether a candidate was picked or not. Standard errors are displayed in parentheses. The estimation is based on 300 scrambled Halton draws.

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

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 7 for those attributes with significant interaction effects, i.e., the transferability of training. We find that risk-averse decision makers 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 ~€1375, and with respect to training that is partly usable in other firms it is still ~€910.

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 the 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

Table 7

Marginal effects of training transferability on training decision for mixed logit model with interaction.

Source: BIBB-CBS 2018, own calculations.

	Interacted model (Marginal effects) Mixed logit Direct costs (1)
Risk-tolerant decision makers	
Training partly transferable	−0.0595*** (0.007)
Training completely transferable	−0.0728*** (0.017)
Risk-averse decision makers	
Training partly transferable	−0.0795*** (0.007)
Training completely transferable	−0.1043*** (0.019)
Observations	12,678

Note: The table presents marginal effects for those attributes with significant interaction effects, i.e., the usability of training in other firms (see Table 6). Effects are presented for decision makers with a risk preference equal to the sample mean increased by half a standard deviation (i.e., risk-tolerant) as well as for decision makers with a risk preference equal to the sample mean reduced by half a standard deviation (i.e., risk-averse). The dependent variable indicates whether the training is offered or not. Standard errors are displayed in parentheses.

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

effects from Table 5 using different model specifications and present the results in Table A.8. 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.9 and A.10, essentially replicate our preferred results in Tables 6 and 7. 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.11, are very similar to our preferred results (see Table 6). 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, sector, and coverage by collective agreements. Table A.12 in the Appendix shows that risk affinity is positively correlated with being male, the owner, and with openness, extraversion, and emotional stability. It is negatively correlated with agreeableness and having a vocational degree. Overall, all correlations are rather small. 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. Carril et al. (2018) apply a similar approach in the context of a regression discontinuity design, and Hofmann et al. (2017) in the context of inverse probability weighting. To the best of our knowledge, we are the first study applying this approach for a vignette design and for a mixed logit model. The corresponding propensity score estimation and the differences in observed attributes with and without weights are reported in Table A.13 in the Appendix. As we do not observe these attributes for all decision makers, the sample becomes slightly smaller. Therefore, we replicate our main results from Table 6 for the smaller sample in column (1) of Table A.14 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.

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). It is also at odds with earlier research showing that women in Germany in the early 2000's participate in training less frequently than men (Caliendo et al., 2022). Future research exploring whether there are gender gaps in training, and, if so, what generates them would be interesting. 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 – as well as other behavioural traits – in real-world settings would be valuable.

In our view, four 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. Third, we need to know more about the way that economic conditions in product and labour markets shape the risks that managers must account for when making both training and other investments. 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.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary tables and figures

Table A.1

Heterogeneity in training incidence and risk affinity by sectors.

Source: BIBB-CBS 2013/2018, own calculations.

Sector	Training firms (1)	Average risk affinity (2)	High competition (3)	Tightness of local LM (4)	Observations (5)
Agriculture (A), Mining (B)	0.48	5.80	0.64	3.87	127
Manufacturing (C)	0.66	5.18	0.67	4.02	588
Energy Supply (D)	0.92	4.46	0.76	3.53	40
Water Supply (E)	0.73	5.30	0.32	3.39	38
Construction (F)	0.72	5.11	0.66	4.35	509
Wholesale, Retail Trade (G)	0.72	5.17	0.78	3.77	888
Transportation (H)	0.77	5.05	0.85	3.62	189
Accommodation Activities (I)	0.57	5.93	0.56	4.17	367
Information Activities (J)	0.77	5.90	0.65	3.72	189
Finance and Insurance (K)	0.73	5.67	0.86	3.75	130
Real Estate Activities (L)	0.68	5.19	0.61	3.62	83
Professional Activities (M)	0.81	4.92	0.65	3.68	454
Administrative Activities (N)	0.70	5.23	0.75	3.87	380
Public Administration (O)	0.95	5.13	0.12	3.19	164
Education (P)	0.82	5.00	0.45	3.33	92
Human Health, Social Work (Q)	0.87	5.21	0.51	3.40	574
Arts, Recreation (R)	0.70	5.74	0.49	3.42	60
Other service Activities (S)	0.73	5.47	0.64	3.96	407
Total	0.72	5.28	0.65	3.85	5,279

Note: Weighted averages for sectors. Column (1) presents share of training firms. Risk affinity is measured on a scale from 0 (low) to 10 (high). Column (3) presents share of firms with high competition. High competition: "Are you exposed to high competitive pressure in your segment of the market" (yes or no). Tightness of Labour Market: "How would you consider the availability (quantity) and fit (quality) of workers on the labour market?" (scale from 1 (low) to 5 (high)).

Table A.2

Description of variables by low/high risk – pooled sample.

Source: BIBB-CBS 2013/2018, own calculations.

	Total as of Table 1 (1)	Risk Affinity		Difference (4)
		Low (2)	High (3)	
Managers' Characteristics:				
Firm Position:				
Owner	0.39	0.36	0.41	-0.05***
CEO	0.14	0.14	0.15	-0.01
Department Head	0.09	0.09	0.09	0.00
Head HR	0.14	0.14	0.13	0.01
Head Commerce	0.06	0.06	0.06	0.00
Head of Training	0.08	0.09	0.07	0.02**
Other Position	0.10	0.12	0.08	0.04***
Decision power:				
Decide alone	0.39	0.36	0.41	-0.05***
Decide together with others	0.49	0.50	0.47	0.03*
Support decision	0.08	0.08	0.07	0.00
Not involved in decision	0.05	0.05	0.04	0.01
Manager gross wage (in Euro)	4,118	4,086	4,154	-68.28
Firm Characteristics:				
Training in Firm	0.72	0.71	0.73	-0.02
Legal status of firm:				
Autonomous Individual Holding	0.63	0.63	0.63	0.00
Independent Part of Enterprise	0.12	0.12	0.13	-0.01
Corporate Headquarter	0.05	0.05	0.06	-0.01
Branch Office	0.10	0.10	0.10	0.00
Foundation, Institution, Authority	0.05	0.06	0.04	0.02**
Something different	0.04	0.04	0.04	0.00
Firm-level institutions:				
Work Council	0.23	0.23	0.23	0.01
Collective Bargaining Coverage	0.44	0.44	0.43	0.01
Firm trains apprentices	0.76	0.76	0.76	0.01
Number of Employees:				
Total number of employees	212	221	204	16.69

(continued on next page)

Table A.2 (continued).

	Total as of Table 1 (1)	Risk Affinity		Difference (4)
		Low (2)	High (3)	
Number of employees: 1–9	0.32	0.32	0.31	0.01
Number of employees: 10–49	0.39	0.38	0.40	–0.02
Number of employees: 50–499	0.24	0.25	0.24	0.02
Number of employees: ≥ 500	0.05	0.05	0.05	0.00
Export Oriented	0.11	0.09	0.12	–0.03***
High Competition	0.69	0.68	0.71	–0.03**
Sector:				
Agriculture (A), Mining (B)	0.02	0.02	0.03	–0.01
Manufacturing (C)	0.11	0.11	0.11	0.00
Energy Supply (D)	0.01	0.01	0.01	0.00
Water Supply (E)	0.01	0.01	0.01	0.00
Construction (F)	0.09	0.09	0.09	0.01
Wholesale, Retail Trade (G)	0.17	0.17	0.17	0.01
Transportation (H)	0.03	0.04	0.03	0.00
Accommodation Activities (I)	0.07	0.06	0.08	–0.01*
Information Activities (J)	0.04	0.03	0.04	–0.01
Finance and Insurance (K)	0.03	0.02	0.03	–0.01
Real Estate Activities (L)	0.02	0.02	0.01	0.00
Professional Activities (M)	0.09	0.10	0.08	0.01
Administrative Activities (N)	0.07	0.07	0.07	0.00
Public Administration (O)	0.03	0.03	0.03	0.01
Education (P)	0.02	0.02	0.02	0.00
Human Health, Social Work (Q)	0.10	0.11	0.10	0.01
Arts, Recreation (R)	0.01	0.01	0.01	0.00
Other service Activities (S)	0.08	0.07	0.08	–0.01
Observations	6,364	3,370	2,994	

Note: Column (1) replicates the result for the total sample, see Table 1, column (3). Column (2)/(3) split the sample of firms by risk affinity of manager. Risk affinity is measured on a scale from 0 (low) to 10 (high). Low risk affinity is defined as smaller or equal to the median, and high risk affinity is defined as greater than the median.

***/**/* indicate statistical significance at the 1%/5%/10%-level according to *t*-test of mean equality.

Table A.3

Regression models (Weighted): Other Investment decisions and risk preferences of decision makers.

Source: BIBB-CBS 2013/2018, own calculations.

	Waves 2013 and 2018		Wave 2013	Wave 2018
	New products (1)	Improved products (2)	New production processes (3)	New computers/machines (4)
Risk Affinity (std)	0.042*** (0.010)	0.053*** (0.009)	0.028** (0.012)	0.049*** (0.014)
Constant	–11.998 (23.580)	–7.424 (25.212)	–1.314*** (0.449)	–0.690 (0.473)
Controls	yes	yes	yes	yes
Observations	5,671	5,671	2,850	2,821

Note: The table displays marginal effects from probit regressions with standard errors in parentheses. The dependent variables are dummies indicating that the firm has introduced new products (column 1), improved its products (column 2), adopted new production processes (column 3) or invested in new computers and machines (column 4). All information are reported for the previous three years. The main explanatory variable of interest is the managers' self-reported standardised risk affinity measured using an 11-point Likert scale. Controls include the respondents' decision power (4 categories), position in firm (7), manager wage (in Euro), the firms' legal status (6), work council (yes/no), collective bargaining (yes/no), training apprentices (yes/no), firm size (4), occupation of worker (2-digit KldB: 35), sector (1-digit NACE: 18), region (16) and wave (2013/2018).

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

Table A.4

Regression models (Unweighted): Training decision (and investment) of Firms and risk preference of decision maker.

Source: BIBB-CBS 2013/2018, own calculations.

	Per-head Investment	Training yes/no	
	Wave 2013	Wave 2018 vignette firms	Wave 2013 and 2018 pooled
	(1)	(2)	(3)
Risk Affinity (std)	0.148*** (0.057)	0.012 (0.012)	0.010* (0.005)
Constant	2.884*** (0.717)	1.582* (0.874)	−74.499*** (17.096)
Controls	yes	yes	yes
Observations	3,042	1,023	6,364

Note: The table displays marginal effects from linear (column 1) and probit regressions (columns 2/3) with standard errors in parentheses. In column (1) the dependent variable is the log of training investment per worker (in Euro). In column (2) and (3) the dependent variable is a dummy indicating whether a firm provides training to their workers. The main explanatory variable of interest is the managers' self-reported standardised risk affinity measured using an 11-point Likert scale. Controls include the respondents' decision power (4 categories), position in firm (7), manager wage (in Euro), the firms' legal status (6), work council (yes/no), collective bargaining (yes/no), training apprentices (yes/no), firm size (4), occupation of worker (2-digit KldB: 35), sector (1-digit NACE: 18), region (16) and wave (2013/2018). No weights applied.

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

Table A.5

Regression models – training in Firms.

Source: BIBB-CBS 2013/2018, own calculations.

	Training Investment		Training yes/no	
	Wave 2013		Wave 2018	
	(1)	(2)	(3)	(4)
Risk Affinity (std)	0.219*** (0.083)	0.212** (0.083)	0.024* (0.013)	0.017 (0.013)
Preference for Future Profits		0.179** (0.083)		
Procrastination		−0.272*** (0.082)		
Locus of Control				0.010 (0.014)
B5 Openness				0.019 (0.015)
B5 Conscientiousness				−0.051*** (0.014)
B5 Extraversion				0.027** (0.014)
B5 Agreeableness				0.039*** (0.013)
B5 Emotional Stability				−0.049*** (0.013)
Observations	3,042	3,042	1,023	992

Note: The table displays marginal effects from linear (columns 1/2) and probit regressions (columns 3/4) with standard errors in parentheses. In column (1) and (2) the dependent variable is the log of training investment per worker (in Euro). In column (3) and (4) the dependent variable is a dummy indicating whether a firm provides training to their workers. The main explanatory variable of interest is the managers' self-reported standardised risk affinity measured using an 11-point Likert scale. Column (1) replicates the results from Table 2 column (1). In Column (2) additional controls for managers' time preferences and the self-reported tendency to procrastinate are included. Column (3) replicates the results from Table 2 column (3). Column (4) includes additional controls for BIG-5 personality traits and Locus of Control. Further controls include the respondents' decision power (4 categories), position in firm (7), manager wage (in Euro), the firms' legal status (6), work council (yes/no), collective bargaining (yes/no), training apprentices (yes/no), firm size (4), occupation of worker (2-digit KldB: 35), sector (1-digit NACE: 18), region (16) and wave (2013/2018).

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

Table A.6

Regression models (Weighted): Training decision of Firms and risk preference of decision maker – split by competition faced by firms and labour market tightness.
Source: BIBB-CBS 2013/2018, own calculations.

	Competition faced by firms		Tightness of local labor market	
	high (1)	low (2)	high (3)	low (4)
Risk affinity (std)	0.020** (0.009)	0.018 (0.012)	0.024** (0.010)	0.014 (0.011)
Controls	yes	yes	yes	yes
Observations	4,369	1,962	3,624	2,419

Note: The table presents marginal effects from probit regressions with standard errors in parentheses. The regressions are re-estimations of the main specification from Table 2 for the sample split by the competition firms face and by labour market tightness. For both variables the sample is split by the median. Controls include the respondents' decision power (4 categories), position in firm (7), manager wage (in Euro), the firms' legal status (6), work council (yes/no), collective bargaining (yes/no), training apprentices (yes/no), firm size (4), occupation of worker (2-digit KldB: 35), sector (1-digit NACE: 18), region (16) and wave (2013/2018).

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

Table A.7

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 Expertise	(1) ... has below average occupational expertise. (2) ... has average occupational expertise. (3) ... has above average occupational expertise.
Job 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 ...
Usability in other firms	(1) ... is only usable in your firm and not in other firms. (2) ... is partly usable also in other firms. (3) ... is completely usable also in other firms.
Training duration	(1) ... takes 2 working days. (2) ... takes 5 working days. (3) ... takes 10 working days.
Cost coverage by the employer	(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. [0.5em]

Note: Overview of possible vignette attributes as implemented in BIBB-CBS 2018.

Table A.8

Robustness analysis 1a: Distribution of random parameters and cost specification.

Source: BIBB-CBS 2018, own calculations.

	Model (Marginal Effects)			
	Conditional Logit	Mixed Logit	Mixed Logit Correlated	Mixed Logit Direct Costs Ln
	(1)	(2)	(3)	(4)
Training Candidate:				
Female	0.0167** (0.007)	0.0107*** (0.001)	0.0087*** (0.002)	0.0088** (0.004)
Age				
25 Years Old	0.1505*** (0.012)	0.1289*** (0.008)	0.1290*** (0.006)	0.1330*** (0.007)
35 Years Old	0.1406*** (0.012)	0.1240*** (0.008)	0.1260*** (0.006)	0.1273*** (0.006)
45 Years Old	0.1174*** (0.012)	0.1039*** (0.008)	0.1029*** (0.005)	0.1055*** (0.004)
Occupational Expertise				
Average	0.0916*** (0.009)	0.0866*** (0.006)	0.0836*** (0.005)	0.0862*** (0.002)
Above Average	0.1564*** (0.012)	0.1310*** (0.009)	0.1165*** (0.006)	0.1315*** (0.012)
Job Mobility	-0.0826*** (0.005)	-0.0640*** (0.002)	-0.0648*** (0.003)	-0.0639*** (0.003)
Training Context:				
Usability in other Firms				
Partly	-0.0742*** (0.009)	-0.0728*** (0.003)	-0.0798*** (0.004)	-0.0713*** (0.002)
Completely	-0.0971*** (0.009)	-0.0906*** (0.004)	-0.0922*** (0.004)	-0.0902*** (0.003)
Training Duration	-0.0090*** (0.002)	-0.0284*** (0.001)	-0.0273*** (0.001)	-0.0180*** (0.009)
Cost Coverage by the Employer				
50 Percent	0.0027 (0.009)	0.0038*** (0.001)	0.0024 (0.002)	
100 Percent	-0.0318*** (0.009)	-0.0303*** (0.001)	-0.0368*** (0.002)	
Direct Costs (for employer)				-0.0188*** (0.004)
Observations	12,678	12,678	12,678	12,678

Note: The table replicates the marginal effects from Table 5 using different model specifications. The dependent variable indicates whether a candidate was picked or not. The displayed values in column (1) are the average marginal effects of the basic conditional logit model without unobserved heterogeneity and using the cost sharing rules as measures of training costs corresponding to column (1) in Table 4. Column (2) shows the average marginal effects corresponding to the basic mixed logit model (see column (2) in Table 4). The average marginal effects in column (3) correspond to the mixed logit model with correlated effects (see column (3) in Table 4). 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 4. Standard errors are displayed in parentheses.

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

Table A.9

Robustness analysis 1b: Distribution of random parameters and cost specification for Interacted Models (parameter estimates)

Source: BIBB-CBS 2018, own calculations.

	Interacted Model		
	Mixed Logit	Mixed Logit Correlated	Mixed Logit Direct Cost Ln
	(1)	(2)	(3)
Mean:			
Training Candidate:			
Female	0.078** (0.038)	0.085 (0.055)	0.066* (0.038)
Age			
25 Years Old	0.850*** (0.072)	1.260*** (0.127)	0.867*** (0.070)
35 Years Old	0.811*** (0.072)	1.178*** (0.126)	0.828*** (0.071)
45 Years Old	0.657*** (0.068)	0.936*** (0.108)	0.663*** (0.066)

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Table A.9 (continued).

	Interacted Model		
	Mixed Logit	Mixed Logit Correlated	Mixed Logit Direct Cost Ln
	(1)	(2)	(3)
Occupational Expertise			
Above Average	0.925*** (0.072)	1.319*** (0.130)	0.920*** (0.069)
Average	0.503*** (0.052)	0.756*** (0.094)	0.495*** (0.051)
Job Mobility	−0.486*** (0.033)	−0.683*** (0.059)	−0.480*** (0.032)
Training Context:			
Usability in other Firms			
Completely	−0.559*** (0.055)	−0.782*** (0.092)	−0.553*** (0.053)
Partly	−0.447*** (0.053)	−0.646*** (0.084)	−0.433*** (0.052)
Cost Coverage by the Employer			
100 Percent	−0.194*** (0.050)	−0.326*** (0.075)	
50 Percent	0.024 (0.051)	0.018 (0.081)	
Training Duration	−0.055*** (0.007)	−0.068*** (0.011)	−0.035*** (0.008)
Direct Costs (for employer)			−0.153*** (0.036)
Interacted with RISK by:			
Training Candidate:			
Female	0.015 (0.038)	0.006 (0.052)	0.015 (0.038)
Age			
25 Years Old	−0.060 (0.065)	−0.080 (0.093)	−0.061 (0.064)
35 Years Old	−0.012 (0.065)	0.002 (0.095)	−0.014 (0.065)
45 Years Old	−0.032 (0.064)	−0.000 (0.088)	−0.031 (0.063)
Occupational Expertise			
Above Average	−0.035 (0.063)	−0.073 (0.099)	−0.035 (0.062)
Average	−0.075 (0.050)	−0.107 (0.078)	−0.071 (0.049)
Job Mobility	0.040 (0.028)	0.081** (0.040)	0.038 (0.028)
Training Context:			
Usability in other Firms			
Completely	0.205*** (0.052)	0.310*** (0.076)	0.205*** (0.051)
Partly	0.136*** (0.050)	0.229*** (0.074)	0.134*** (0.049)
Training Duration	−0.002 (0.007)	−0.000 (0.009)	−0.005 (0.008)
Cost Coverage by the Employer			
100 Percent	0.013 (0.050)	0.012 (0.071)	
50 Percent	−0.053 (0.051)	−0.071 (0.072)	
Direct Costs (for employer)			−0.014 (0.036)
SD			
Female	0.423*** (0.090)	0.650*** (0.124)	0.438*** (0.086)
Age			
25 Years Old	0.505*** (0.152)	1.072*** (0.209)	−0.469*** (0.157)
35 Years Old	0.504*** (0.143)	1.373*** (0.201)	0.508*** (0.148)

(continued on next page)

Table A.9 (continued).

	Interacted Model		
	Mixed Logit	Mixed Logit Correlated	Mixed Logit Direct Cost Ln
	(1)	(2)	(3)
45 Years Old	−0.321 (0.207)	0.926*** (0.178)	−0.291 (0.213)
Occupational Expertise			
Above Average	1.177*** (0.090)	2.380*** (0.201)	1.163*** (0.088)
Average	−0.071 (0.178)	1.321*** (0.149)	0.014 (0.175)
Job Mobility	0.352*** (0.059)	0.480*** (0.085)	0.361*** (0.056)
Usability in other Firms			
Completely	−0.287* (0.155)	1.011*** (0.178)	0.229 (0.213)
Partly	−0.154 (0.175)	0.915*** (0.162)	0.073 (0.245)
Cost Coverage by the Employer			
100 Percent	0.035 (0.204)	0.886*** (0.146)	
50 Percent	−0.180 (0.263)	0.731*** (0.185)	
Training Duration	0.098*** (0.014)	0.138*** (0.022)	0.096*** (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: The table displays means and standard deviations (SD) based on logit models with their corresponding standard errors in parentheses. All models allow the observed attributes of choice alternatives to be fully interacted with our standardized, continuous measure of decision makers' risk aversion. Estimations are based on 300 scrambled Halton draws.

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

Table A.10

Robustness analysis 1c: Distribution of random parameters and cost specification for Interacted Models (Marginal Effects)

Source: BIBB-CBS 2018, own calculations.

	Interacted Model (Marginal Effects)		
	Mixed Logit	Mixed Logit Correlated	Mixed Logit Direct Costs Ln
	(1)	(2)	(3)
Risk-tolerant decision makers			
Training partly transferable	−0.061*** (0.012)	−0.062 (0.001)	−0.059*** (0.007)
Training completely transferable	−0.073*** (0.021)	−0.072 (0.001)	−0.073*** (0.016)
Risk-averse decision makers			
Training partly transferable	−0.081*** (0.013)	−0.085 (0.001)	−0.079*** (0.006)
Training completely transferable	−0.104*** (0.024)	−0.105 (0.002)	−0.104*** (0.017)
Observation	12,678	12,678	12,678

Note: This table replicates the results from Table 7 using different model specifications (as presented in Table 4). The presented values are average marginal effects of those attributes with significant interaction effects, i.e., the transferability of the training to other firms (see Table 6). The dependent variable indicates whether the training is offered or not. Column (1) is a mixed restricted logit model with uncorrelated random coefficients. Column (2) is a correlated mixed logit model that is estimated using an unrestricted variance-covariance matrix for random parameters. Both column (1) and (2) assume that the unobserved heterogeneity follows a multivariate normal distribution. Column (3) is specified as column (1) but includes direct training costs rather than the cost sharing rule. Effects are presented for decision makers with a risk preference equal to the sample mean increased by half a standard deviation (i.e., risk-tolerant) as well as for decision makers with a risk preference equal to the sample mean reduced by half a standard deviation (i.e., risk-averse). Standard errors are displayed in parentheses.

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

Table A.11

Robustness analysis 2: Interacted Models with Risk-High Dummy (parameter estimates)

Source: BIBB-CBS 2018, own calculations.

	Interacted Model with Risk-High Dummy			
	Mixed Logit Direct Costs	Mixed Logit Logit	Mixed Logit Correlated	Mixed Logit Direct Costs Ln
	(1)	(2)	(3)	(4)
Mean:				
Training Candidate:				
Female	0.025 (0.047)	0.053 (0.069)	0.035 (0.048)	0.025 (0.047)
Age				
25 Years Old	0.866*** ((0.085)	1.304*** (0.149)	0.849*** (0.087)	0.866*** (0.085)
35 Years Old	0.786*** ((0.085)	1.168*** (0.145)	0.772*** (0.086)	0.786*** (0.085)
45 Years Old	0.651*** (0.081)	0.918*** (0.127)	0.649*** (0.083)	0.651*** (0.081)
Occupational Expertise				
Above Average	0.981*** (0.083)	1.465*** (0.153)	0.989*** (0.086)	0.981*** (0.083)
Average	0.578*** (0.063)	0.934*** (0.116)	0.588*** (0.065)	0.578*** (0.063)
Job Mobility	-0.495*** (0.038)	-0.747*** (0.069)	-0.501*** (0.039)	-0.495*** (0.038)
Training Context:				
Usability in other Firms				
Completely	-0.715*** (0.067)	-1.031*** (0.113)	-0.722*** (0.069)	-0.715*** (0.067)
Partly	-0.506*** (0.064)	-0.786*** (0.105)	-0.520*** (0.066)	-0.506*** (0.064)
Cost Coverage by the Employer				
100 Percent		-0.357*** (0.095)	-0.205*** (0.063)	
50 Percent		0.019 (0.098)	0.053 (0.064)	
Training Duration	-0.033*** (0.010)	-0.073*** (0.014)	-0.054*** (0.009)	-0.033*** (0.010)
Direct Costs (for employer)	-0.154*** (0.045)			-0.154*** (0.045)
Interaction with Risk-High by:				
Training Candidate:				
Female	0.107 (0.078)	0.094 (0.107)	0.112 (0.078)	0.107 (0.078)
Age				
25 Years Old	-0.013 (0.131)	-0.004 (0.196)	-0.015 (0.132)	-0.013 (0.131)
35 Years Old	0.098 (0.133)	0.160 (0.200)	0.093 (0.134)	0.098 (0.133)
45 Years Old	0.016 (0.129)	0.126 (0.188)	0.007 (0.130)	0.016 (0.129)
Occupational Expertise				
Above Average	-0.173 (0.128)	-0.279 (0.212)	-0.179 (0.130)	-0.173 (0.128)
Average	-0.230** (0.100)	-0.348** (0.165)	-0.235** (0.102)	-0.230** (0.100)
Job Mobility	0.042 (0.057)	0.103 (0.081)	0.046 (0.057)	0.042 (0.057)
Training Context:				
Usability in other Firms				
Completely	0.451*** (0.105)	0.697*** (0.158)	0.452*** (0.106)	0.451*** (0.105)
Partly	0.199* (0.102)	0.375** (0.150)	0.200* (0.103)	0.199* (0.102)
Training Duration	-0.005 (0.017)	-0.000 (0.019)	-0.003 (0.014)	-0.005 (0.017)

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Table A.11 (continued).

	Interacted Model with Risk-High Dummy			
	Mixed Logit Direct Costs	Mixed Logit	Mixed Logit Correlated	Mixed Logit Direct Costs Ln
	(1)	(2)	(3)	(4)
Cost Coverage by the Employer				
100 Percent		0.043 (0.146)	0.038 (0.102)	
50 Percent		−0.034 (0.151)	−0.081 (0.106)	
Direct Costs (for employer)	−0.010 (0.073)			−0.010 (0.073)
SD:				
Female	0.423*** (0.088)	0.595*** (0.121)	0.408*** (0.091)	0.423*** (0.088)
Age				
25 Years Old	−0.464*** (0.157)	1.234*** (0.191)	0.494*** (0.153)	−0.464*** (0.157)
35 Years Old	0.512*** (0.145)	1.427*** (0.200)	0.506*** (0.141)	0.512*** (0.145)
45 Years Old	−0.277 (0.218)	1.044*** (0.209)	−0.303 (0.213)	−0.277 (0.218)
Occupational Expertise				
Above Average	1.163*** (0.087)	2.375*** (0.193)	1.175*** (0.089)	1.163*** (0.087)
Average	0.008 (0.174)	1.352*** (0.149)	−0.072 (0.176)	0.008 (0.174)
Job Mobility	0.358*** (0.056)	0.509*** (0.082)	0.351*** (0.058)	0.358*** (0.056)
Usability in other Firms				
Completely	0.212 (0.231)	0.998*** (0.159)	−0.264 (0.164)	0.212 (0.231)
Partly	0.063 (0.246)	0.957*** (0.147)	−0.139 (0.178)	0.063 (0.246)
Cost Coverage by the Employer				
100 Percent		0.837*** (0.152)	0.045 (0.200)	
50 Percent		0.784*** (0.163)	−0.194 (0.250)	
Training Duration	0.096*** (0.013)	0.139*** (0.019)	0.097*** (0.014)	0.096*** (0.013)
Direct Costs (for employer)	0.000 (0.137)			0.000 (0.163)
Observations	12,678	12,678	12,678	12,678
Log-Likelihood	−3,791	−3,672	−3,788	−3,791
Number of Draws	300	300	300	300

Note: This table replicates the results from Table A.6 and Table A.9 using an alternative specification for decision makers risk preferences. 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.

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

Table A.12

Correlation between risk affinity and other individual characteristics/preferences
– vignette firms.

Source: BIBB-CBS 2018, own calculations.

Other characteristics	Pairwise correlations with risk affinity
Locus of Control	0.16***
B5 Openness	0.29***
B5 Conscientiousness	0.04
B5 Extraversion	0.28***
B5 Agreeableness	−0.08**
B5 Emotional Stability	0.22***
Altruism	0.10***
Reciprocity (positive)	−0.01
Male	0.09***

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Table A.12 (continued).

Other characteristics	Pairwise correlations with risk affinity
Firm Tenure (in Years)	−0.05*
Educational Status:	
No Vocational Degree	0.00
Vocational Degree	−0.07**
Advanced Voc. Degree	0.00
Academic Degree	0.05*
Firm Position:	
Owner	0.08***
CEO	0.03
Department Head	0.01
Head HR	0.02
Head Commerce	−0.02
Head of Training	−0.04
Other Position	−0.13***
Decision power:	
Decide alone	0.07**
Decide together with others	0.02
Support decision	−0.05
Not involved in decision	−0.08***
Manager wage	−0.02

Note: The table shows correlation coefficients between risk affinity and other individual characteristics/preferences of managers.

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

Table A.13

Robustness analysis 3a: Propensity score estimation and matching quality.

Source: BIBB-CBS 2018, own calculations. Standard errors in parentheses.

	Logit Estimation	MSB (%bias)		t-test	
	P(Risk-Median = 1)	Unmatched	Matched	t-value	p-value
	(1)	(2)	(3)	(4)	(5)
Firm Position:					
Owner	0.760*** (0.101)	16.4	2.2	0.97	0.333
CEO	0.599*** (0.103)	8.3	−4.6	−1.97	0.049
Department Head	0.411*** (0.115)	8.1	0.9	0.38	0.704
Head HR	0.274** (0.096)	−1.1	−5.3	−2.38	0.018
Head Commerce	−0.158 (0.117)	−13.4	3.5	1.83	0.067
Head of Training	−0.469*** (0.121)	−15.3	0.3	0.16	0.871
Other Position	Ref.	−16.7	4.3	2.30	0.022
Firm Tenure in Years	−0.015*** (0.002)	−9.0	−1.6	−0.76	0.448
Educational Status:					
No Vocational Degree	1.065*** (0.272)	4.5	−1.9	−0.74	0.462
Vocational Degree	−0.019 (0.064)	−1.4	4.3	2.02	0.043
Advanced Voc. Degree	−0.003 (0.057)	−5.3	−0.2	−0.10	0.923
Academic Degree	Ref.	5.5	−3.0	−1.36	0.172
Firm's Training Decision:					
Alone	−0.001 (0.109)	15.7	3.0	1.32	0.185
Together	−0.072 (0.098)	−5.9	0.3	0.12	0.907
Support	0.162 (0.105)	−3.6	−4.4	−2.00	0.046

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Table A.13 (continued).

	Logit Estimation	MSB (%bias)		<i>t</i> -test	
	<i>P</i> (Risk-Median = 1)	Unmatched	Matched	<i>t</i> -value	<i>p</i> -value
	(1)	(2)	(3)	(4)	(5)
Not Involved	Ref.	−11.3	0.3	0.16	0.874
Reciprocity	−0.076*** (0.019)	−2.4	4.8	2.12	0.034
Internal Locus of Control	0.494*** (0.035)	36.1	10.8	5.25	0.000
Big Five:					
Openness	0.477*** (0.026)	51.8	−1.9	−0.93	0.354
Conscientiousness	−0.165*** (0.031)	2.7	7.2	3.20	0.001
Extraversion	0.356*** (0.022)	53.3	2.5	1.19	0.235
Agreeableness	−0.425*** (0.026)	−23.2	4.6	2.00	0.045
Emotional Stability	0.157*** (0.022)	26.7	8.1	3.90	0.000
Number of Employees in Firm	0.000* (0.000)	−3.6	0.5	0.25	0.801
Vocational Training Provider	−0.099* (0.052)	−6.7	−1.8	−0.80	0.426
Firm:					
Export Oriented	0.565*** (0.081)	12.8	3.3	1.43	0.152
High Competition	0.011 (0.051)	0.8	−0.9	−0.41	0.682
Training Cooperations	−0.058 (0.053)	9.0	−1.3	−0.56	0.682
Profit Sharing	0.087* (0.049)	12.3	2.2	1.00	0.319
Flexible Work Hours	0.359*** (0.050)	11.8	−0.8	−0.36	0.715
Legal Status of the Firm:					
Autonomous Individual Holding	−0.158 (0.122)	1.2	−1.2	−0.54	0.591
Independent Operation as Part of Enterprise	0.292** (0.135)	5.8	−1.1	−0.49	0.623
Corporate Headquarter	−0.167 (0.145)	−4.2	−3.4	−1.57	0.117
Branch Office	0.460*** (0.140)	7.6	4.0	1.78	0.075
Foundation, Institution, Authority	−0.748*** (0.201)	−11.1	0.7	0.36	0.720
Something different	Ref.	−6.6	2.5	1.28	0.200
Firm's Utilized Capacity	−0.008*** (0.002)	−3.8	−0.5	−0.23	0.822
Sector:					
Agriculture (A)	0.203 (0.189)	−3.0	0.6	0.27	0.786
Manufacturing (C)	0.455*** (0.108)	6.6	2.6	0.27	0.786
Water Supply (E)	−0.146 (0.356)	−5.4	−0.6	−0.35	0.728
Construction (F)	0.548*** (0.111)	0.9	−5.8	−2.52	0.012
Wholesale, Retail Trade (G)	0.453*** (0.097)	0.8	2.6	1.19	0.233
Transportation (H)	−0.019 (0.153)	−5.9	−1.0	−0.51	0.610
Accommodation Activities (I)	0.508*** (0.116)	10.1	−4.9	−2.01	0.044
Information Activities (J)	0.476*** (0.137)	2.1	−3.9	−1.66	0.097

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Table A.13 (continued).

	Logit Estimation	MSB (%bias)		<i>t</i> -test	
	<i>P</i> (Risk-Median = 1)	Unmatched	Matched	<i>t</i> -value	<i>p</i> -value
	(1)	(2)	(3)	(4)	(5)
Finance and Insurance (K)	0.464** (0.158)	7.5	3.3	1.43	0.154
Real Estate Activities (L)	0.114 (0.204)	−6.6	−1.3	−0.66	0.508
Professional Activities (M)	0.403*** (0.110)	−4.2	1.4	0.65	0.514
Administrative Activities (N)	0.429*** (0.116)	3.8	6.1	2.87	0.004
Public Administration (O)	1.474*** (0.214)	−1.4	0.9	0.41	0.679
Education (P)	−0.430* (0.256)	−12.5	0.5	0.33	0.740
Human Health, Social Work (Q)	0.339*** (0.102)	−2.7	−3.1	−1.42	0.115
Arts, Recreation (R)	0.191 (0.257)	0.5	4.8	2.52	0.012
Other service Activities (S)	−0.035 (0.125)	−1.8	1.4	0.66	0.510
Other Branches (incl. Mining B, Electricity C)	Ref.	−2.9	−0.2	−0.11	0.911
Work Council	−0.277*** (0.069)	−9.5	1.7	0.81	0.420
Collective Bargaining Coverage	0.363*** (0.052)	6.3	−3.1	−1.42	0.155
Constant	−4.787*** (0.356)				
Observations	960				
Sample	Ps R2	LR chi2	<i>p</i> > <i>chi</i> 2	Mean Bias	B
Unmatched	0.154	2319.39	0.00	9.3	98.4
Matched	0.011	122.48	0.00	2.7	24.3

Note: 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).

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

Table A.14

Robustness analysis 3b: Parameter estimates of mixed logit model with interaction with and without weights.

Source: BIBB-CBS 2018, own calculations.

	Interacted Model	
	Mixed Logit Direct Costs Unweighted	Mixed Logit Direct Costs Weighted
	(1)	(2)
Mean:		
Training Candidate:		
Female	0.065 (0.040)	0.051 (0.081)
Age		
25 Years Old	0.877*** (0.075)	1.004*** (0.143)
35 Years Old	0.830*** (0.075)	0.862*** (0.140)
45 Years Old	0.667*** (0.069)	0.748*** (0.133)
Occupational Expertise		
Above Average	0.961***	1.093***

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Table A.14 (continued).

	Interacted Model	
	Mixed Logit Direct Costs Unweighted	Mixed Logit Direct Costs Weighted
	(1)	(2)
Average	(0.073) 0.505*** (0.054)	(0.148) 0.645*** (0.104)
Job Mobility	−0.500*** (0.035)	−0.637*** (0.071)
Training Context:		
Usability in other Firms		
Completely	−0.525*** (0.055)	−0.926*** (0.111)
Partly	−0.428*** (0.054)	−0.665*** (0.100)
Training Duration	−0.034*** (0.009)	−0.028* (0.016)
Direct Costs (for employer)	0.150*** (0.038)	0.162** (0.080)
Interacted with RISK by: Training Candidate:		
Female	0.033 (0.040)	0.102 (0.104)
Age		
25 Years Old	−0.042 (0.068)	−0.068 (0.183)
35 Years Old	0.002 (0.069)	0.074 (0.183)
45 Years Old	−0.017 (0.065)	−0.041 (0.172)
Occupational Expertise		
Above Average	−0.046 (0.064)	−0.225 (0.185)
Average	−0.075 (0.052)	−0.286** (0.138)
Job Mobility	0.051* (0.029)	0.170** (0.080)
Training Context:		
Usability in other Firms		
Completely	0.187*** (0.053)	0.656*** (0.142)
Partly	0.143*** (0.052)	0.365*** (0.132)
Training Duration	−0.005 (0.009)	−0.007 (0.022)
Direct Costs (for employer)	−0.021 (0.037)	−0.014 (0.100)
SD:		
Female	0.447*** (0.089)	0.496*** (0.107)
Age		
25 Years Old	0.500*** (0.163)	0.527*** (0.172)
35 Years Old	0.591*** (0.142)	0.671*** (0.161)
45 Years Old	0.112 (0.356)	0.044 (0.091)
Occupational Expertise		
Above Average	1.174*** (0.092)	1.187*** (0.115)
Average	−0.156 (0.146)	−0.213* (0.128)
Job Mobility	0.395*** (0.055)	0.447*** (0.069)

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Table A.14 (continued).

	Interacted Model	
	Mixed Logit Direct Costs Unweighted	Mixed Logit Direct Costs Weighted
	(1)	(2)
Usability in other Firms		
Completely	0.223 (0.199)	0.331** (0.158)
Partly	0.113 (0.236)	−0.164 (0.177)
Training Duration	0.098*** (0.014)	0.095*** (0.018)
Direct Costs (for employer)	−0.092 (0.125)	−0.135 (0.106)
Observations	11,842	11,842
Log-Likelihood	−3,537	−2,547
Number of Draws	300	300

Note: In this table we replicate the analysis from Table 6 for all observations where the conditioning variables are not missing. The sample size decreases by 836 observations. In Column (1) no weights are applied. In Column (2) we apply weights that equalize the differences in the observed personal and firm characteristics of risk-averse and risk-tolerant managers. Standard errors in parentheses. Estimation based on 300 scrambled Halton draws.

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

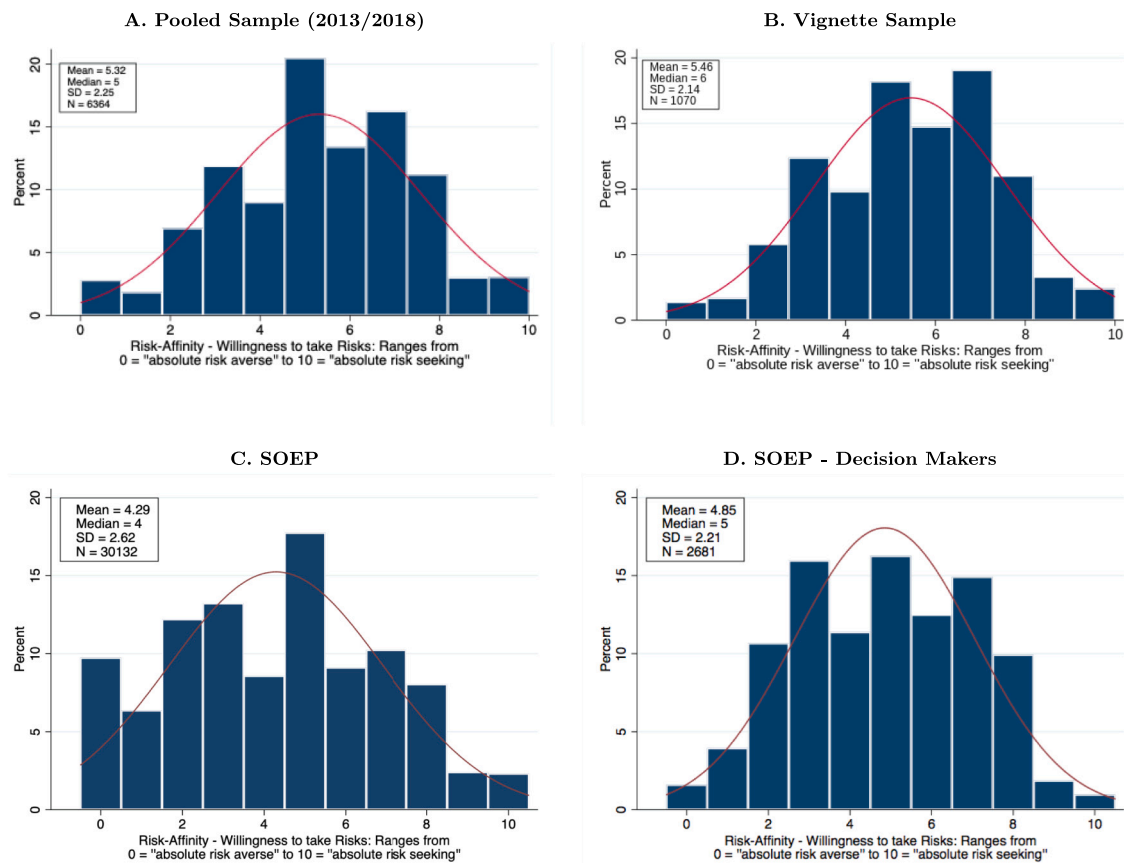


Fig. A.1. Distribution of Risk Tolerance in Our Sample and the German Population.

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

Appendix B. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.euroecorev.2023.104616>.

References

- Abatecola, G., Mandarelli, G., Poggesi, S., 2013. The personality factor: how top management teams make decisions. A literature review. *J. Manag. Gov.* 17 (4), 1073–1100.
- Abdel-Khalik, A.R., 2014. CEO risk preference and investing in R&D. *Abacus* 50 (3), 245–278.
- Acemoglu, D., 1997. Training and innovation in an imperfect labour market. *Rev. Econom. Stud.* 64 (3), 445–464.
- Acemoglu, D., Pischke, J.-S., 1998. Why do firms train? Theory and evidence. *Q. J. Econ.* 113 (1), 79–119.
- Acemoglu, D., Pischke, J.-S., 1999a. Beyond becker: Training in imperfect labour markets. *Econom. J.* 109 (453), 112–142.
- Acemoglu, D., Pischke, J.-S., 1999b. The structure of wages and investment in general training. *J. Polit. Econ.* 107 (3), 539–572.
- Adhvaryu, A., Kala, N., Nyshadham, A., 2022. Management and shocks to worker productivity. *J. Polit. Econ.* 130 (1), 1–47.
- Adhvaryu, A., Nyshadham, A., Tamayo, J., 2023. Managerial quality and productivity dynamics. *Rev. Econom. Stud.* 90 (4), 1569–1607.
- Alfonsi, L., Bandiera, O., Bassi, V., Burgess, R., Rasul, I., Sulaiman, M., Vitali, A., 2020. Tackling youth unemployment: Evidence from a labor market experiment in Uganda. *Econometrica* 88 (6), 2369–2414.
- Almeida, R., Behrman, J., Robalino, D., 2012. *The Right Skills for the Job?*. World Bank Publications, Washington D.C., US.
- Arulampalam, W., Booth, A., 1997. Who gets over the training hurdle? A study of the training experiences of young men and women in Britain. *J. Popul. Econ.* 10 (2), 197–217.
- Asplund, R., 2005. The provision and effects of company training: A brief review of the literature. *Nord. J. Political Econ.* 31, 47–73.
- Bandiera, O., Prat, A., Hansen, S., Sadun, R., 2020. CEO behavior and firm performance. *J. Polit. Econ.* 128 (4), 1325–1369.
- Barr, S.H., Hitt, M.A., 1986. A comparison of selection decision models in manager versus student samples. *Pers. Psychol.* 39 (3), 599–617.
- Barrett, A., O'Connell, P.J., 2001. Does training generally work? the returns to in-company training. *ILR Rev.* 54 (3), 647–662.
- Barsky, R.B., Juster, F.T., Kimball, M.S., Shapiro, M.D., 1997. Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *Q. J. Econ.* 112 (2), 537–579.
- Bartel, A.P., 2000. Measuring the employer's return on investments in training: evidence from the literature. *Ind. Relat.: J. Econ. Soc.* 39 (3), 502–524.
- Basiglio, S., Ricci, A., Rossi, M.C., 2023. Bosses' Impatience and Digital Technologies. Working Paper 98, Inapp.
- Bassanini, A., Booth, A., Brunello, G., Paola, M.D., Leuven, E., 2007. Workplace training in Europe. In: Brunello, G., Garibaldi, P., Wasmer, E. (Eds.), *Education and Training in Europe*. Oxford University Press, Oxford and New York, pp. 143–323.
- Becker, G.S., 1962. Investment in human capital: A theoretical analysis. *J. Polit. Econ.* 70 (5, Part 2), 9–49.
- Beham, B., Baierl, A., Poelmans, S., 2015. Managerial telework allowance decisions – a vignette study among German managers. *Int. J. Hum. Resour. Manag.* 26 (11), 1385–1406.
- Bertrand, M., Schoar, A., 2003. Managing with style: The effect of managers on firm policies. *Q. J. Econ.* 118 (4), 1169–1208.
- Bhat, C.R., 2001. Quasi-random maximum simulated likelihood estimation of the mixed multinomial logit model. *Transp. Res. B* 35 (7), 677–693.
- Bhat, C.R., 2003. Simulation estimation of mixed discrete choice models using randomised and scrambled Halton sequences. *Transp. Res. B* 37 (9), 837–855.
- Bishop, J.H., 1996. What we know about employer-provided training: A review of the literature. *Res. Labor Econ.* 16, 19–87.
- Black, S., Lynch, L.M., 2004. What's driving the new economy: The benefits of workplace innovation. *Econom. J.* 114 (493), F97–F116.
- Bloom, N., Brynjolfsson, E., Foster, L., Jarmin, R., Patnaik, M., Saporta-Eksten, I., Van Reenen, J., 2019. What drives differences in management practices? *Amer. Econ. Rev.* 109 (5), 1648–1683.
- Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., Roberts, J., 2013. Does management matter? evidence from India. *Q. J. Econ.* 128 (1), 1–51.
- Bloom, N., Van Reenen, J., 2007. Measuring and explaining management practices across firms and countries. *Q. J. Econ.* 122 (4), 1351–1408.
- Booth, A., Bryan, M.L., 2007. Who pays for general training in private sector Britain? *Res. Labour Econ.* 26, 85–123.
- Booth, A.L., Zoega, G., 2000. Why do Firms Invest in General Training? 'Good' Firms and 'Bad' Firms as a Source of Monopsony Power. Discussion Paper 2536, CEPR, London.
- Brenner, S., 2015. The risk preferences of US executives. *Manage. Sci.* 61 (6), 1344–1361.
- Brown, J.L., Martin, P.R., Sprinkle, G.B., Way, D., 2023. How return on investment and residual income performance measures and risk preferences affect risk-taking. *Manage. Sci.* 69 (2), 1301–1322.
- Buers, C., Karpinska, K., Schippers, J., 2018. Managers' retention decisions regarding young intermediate-level educated employees. *Int. J. Manpow.* 39 (2), 254–268.
- Caicedo, S., Espinosa, M., Seibold, A., 2022. Unwilling to train? Firm responses to the Colombian apprenticeship regulation. *Econometrica* 90 (2), 507–550.
- Caliendo, M., Cobb-Clark, D., Obst, C., Seitz, H., Uhlenhorff, A., 2022. Locus of control and investment in training. *J. Hum. Resour.* 57 (4), 1311–1349.
- Carlsson, F., Martinsson, P., 2003. Design techniques for stated preference methods in health economics. *Health Econ.* 12 (4), 281–294.
- Carril, A., Cazor, A., Gerardino, M., Litschig, S., Pomeranz, D., 2018. Subgroup Analysis in Regression Discontinuity Designs. Working Paper.
- Carson, R.T., Graff Zivin, J., Louviere, J.J., Sadoff, S., Shrader, J.G., 2022. The risk of caution: Evidence from an experiment. *Manage. Sci.* 68 (12), 9042–9060.
- Crosetto, P., Filippin, A., 2013. The “bomb” risk elicitation task. *J. Risk Uncertain.* 47 (1), 31–65.
- Dave, C., Eckel, C.C., Johnson, C.A., Rojas, C., 2010. Eliciting risk preferences: When is simple better? *J. Risk Uncertain.* 41 (3), 219–243.
- Dearden, L., Reed, H., Reenen, J.V., 2006. The impact of training on productivity and wages: Evidence from british panel data. *Oxf. Bull. Econ. Stat.* 68 (4), 397–421.
- Dietz, D., Zwick, T., 2020. The retention effect of training: Portability, visibility, and credibility. *Int. J. Hum. Resour. Manag.* 33 (4), 710–741.
- Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., Wagner, G.G., 2011. Individual risk attitudes: Measurement, determinants, and behavioral consequences. *J. Eur. Econom. Assoc.* 9 (3), 522–550.
- Donkers, B., Melenberg, B., Van Soest, A., 2001. Estimating risk attitudes using lotteries: A large sample approach. *J. Risk Uncertain.* 22 (2), 165–195.
- Eckel, C.C., Grossman, P.J., 2002. Sex differences and statistical stereotyping in attitudes toward financial risk. *Evol. Hum. Behav.* 23 (4), 281–295.
- Ellguth, P., Kohaut, S., 2021. Tarifbindung Und Betriebliche Interessenvertretung - Ergebnisse Aus Dem IAB-Betriebspanel 2020. Tech. Rep, IAB, Nuremberg.
- Eriksson, T., Kristensen, N., 2014. Wages or fringes? some evidence on trade-offs and sorting. *J. Labor Econ.* 32 (4), 899–928.
- Fenizia, A., 2022. Managers and productivity in the public sector. *Econometrica* 90 (3), 1063–1084.
- Fleischmann, M., Koster, F., 2017. Older workers and employer provided training in the Netherlands: a vignette study. *Ageing Soc.* 38 (10), 1995–2018.
- Franz, W., Soskice, D., 1995. The German apprenticeship system. In: *Institutional frameworks and labor market performance: comparative views on the US and German economies*. pp. 208–234.
- Frazis, H., Gittleman, M., Joyce, M., 2000. Correlates of training: An analysis using both employer and employee characteristics. *ILR Rev.* 53 (3), 443–462.
- Frazis, H., Loewenstein, M.A., 2007. On-the-job Training. *Found. Trends Microecon.* 2 (5), 363–440.
- Frederiksen, A., Kahn, L.B., Lange, F., 2020. Supervisors and performance management systems. *J. Polit. Econ.* 128 (6), 2123–2187.
- Garavan, T.N., 2007. A strategic perspective on human resource development. *Adv. Dev. Hum. Resour.* 9 (1), 11–30.

- Gersbach, H., Schmutzler, A., 2012. Product markets and industry-specific training. *Rand J. Econ.* 43 (3), 475–491.
- Graham, J.R., Harvey, C.R., Puri, M., 2013. Managerial attitudes and corporate actions. *J. Financ. Econ.* 109 (1), 103–121.
- Grip, A.D., Sauermann, J., 2012. The effects of training on own and co-worker productivity: Evidence from a field experiment. *Econom. J.* 122 (560), 376–399.
- Haan, P., Uhlenhorff, A., 2006. Estimation of multinomial logit models with unobserved heterogeneity using maximum simulated likelihood. *Stata J.* 6 (2), 229–245.
- Haegele, I., 2022. Talent Hoarding in Organizations. Working Paper, arxiv:2206.15098v1, arXiv.org.
- Haelermans, C., Borghans, L., 2012. Wage effects of on-the-job training: A meta-analysis. *Br. J. Ind. Relat.* 50 (3), 502–528.
- Hainmueller, J., Hangartner, D., Yamamoto, T., 2015. Validating vignette and conjoint survey experiments against real-world behavior. *Proc. Natl. Acad. Sci.* 112 (8), 2395–2400.
- Hall, C.M., Pedace, R., 2016. Do managers matter? manager effects on organization performance. *Manag. Decis. Econ.* 37 (8), 541–551.
- Hashimoto, M., 1981. Firm-specific human capital as a shared investment. *Amer. Econ. Rev.* 71 (3), 475–482.
- Hoffman, M., Burks, S.V., 2017. Training Contracts, Employee Turnover, and the Returns from Firm-sponsored General training. Tech. Rep, National Bureau of Economic Research.
- Hoffman, M., Tadelis, S., 2021. People management skills, employee attrition, and manager rewards: An empirical analysis. *J. Polit. Econ.* 129 (1), 243–285.
- Hofmann, B., Kreyenfeld, M., Uhlenhorff, A., 2017. Job displacement and first birth over the business cycle. *Demography* 54 (3), 933–959.
- Hole, A.R., 2007. Fitting mixed logit models by using maximum simulated likelihood. *Stata J.* 7 (3), 388–401.
- Hole, A.R., 2015a. DCREATE: Stata Module to Create Efficient Designs for Discrete Choice Experiments. Statistical Software Components S458059, revised 25 Aug 2017.
- Hole, A.R., 2015b. Mixlogitwtp: stata Module to Estimate Mixed Logit Models in WTP Space. Statistical Software Components S458037, revised 20 Apr 2016.
- Hole, A.R., Kolstad, J.R., 2012. Mixed logit estimation of willingness to pay distributions: A comparison of models in preference and WTP space using data from a health-related choice experiment. *Empir. Econ.* 42 (2), 445–469.
- Holt, C.A., Laury, S.K., 2002. Risk aversion and incentive effects. *Amer. Econ. Rev.* 92 (5), 1644–1655.
- Huber, J., Zwerina, K., 1996. The importance of utility balance in efficient choice designs. *J. Mar. Res.* 33 (3), 307–317.
- Humburg, M., van der Velden, R., 2014. Skills and the Graduate Recruitment Process: evidence from Two Discrete Experiments. Tech. Rep.
- Ichniowski, C., Shaw, K., 1999. The effects of human resource management systems on economic performance: An international comparison of US and Japanese plants. *Manage. Sci.* 45 (5), 704–721.
- Ichniowski, C., Shaw, K., Prennushi, G., 1997. The effects of human resource management practices on productivity: A study of steel finishing lines. *Amer. Econ. Rev.* 87 (3), 291–313.
- Inkinen, H., 2016. Review of empirical research on knowledge management practices and firm performance. *J. Knowl. Manag.* 20 (2), 230–257.
- International Labour Organization, 2008. Conclusions on Skills for Improved Productivity, Employment Growth and Development. Report for the International Labor Conference, ILO, Geneva.
- International Labour Organization, 2011. A Skilled Workforce for Strong, Sustainable and Balanced Growth. A G20 Training Strategy, ILO, Geneva.
- Jansen, A., Pfeifer, H., Raecke, J., 2017. Only the Brave? Risk and Time Preferences of Decision Makers and Firms' Investment in Worker Training. Working Paper No. 124, Swiss Leading House.
- Karpavičius, S., Yu, F., 2019. Managerial risk incentives and a firm's financing policy. *J. Bank. Financ.* 100, 167–181.
- Karpinska, K., Henkens, K., Schippers, J., 2011. The recruitment of early retirees: a vignette study of the factors that affect managers' decisions. *Ageing Soc.* 31 (4), 570.
- Karpinska, K., Henkens, K., Schippers, J., Wang, M., 2015. Training opportunities for older workers in the Netherlands: A Vignette Study. *Res. Soc. Stratif. Mobil.* 41, 103–112.
- Katz, E., Ziderman, A., 1990. Investment in general training: the role of information and labour mobility. *Econom. J.* 100 (403), 1147–1158.
- Kessler, A.S., Lülfesmann, C., 2006. The theory of human capital revisited: on the interaction of general and specific investments. *Econom. J.* 116 (514), 903–923.
- Kolenikov, S., 2012. Scrambled Halton sequences in Mata. *Stata J.* 12 (1), 29–44.
- Kübler, D., Schmid, J., Stüber, R., 2018. Gender discrimination in hiring across occupations: a nationally-representative vignette study. *Labour Econ.* 55, 215–229.
- Lazear, E.P., 2009. Firm-specific human capital: A skill-weights approach. *J. Polit. Econ.* 117 (5), 914–940.
- Lazear, E.P., Shaw, K.L., Stanton, C.T., 2015. The value of bosses. *J. Labor Econ.* 33 (4), 823–861.
- Leuven, E., 2005. The economics of private sector training: A survey of the literature. *J. Econ. Surv.* 19 (1), 91–111.
- Leuven, E., Oosterbeek, H., 1999. Demand and supply of work-related training: evidence from four countries. *Res. Labor Econ.* (18), 303–330.
- Levhari, D., Weiss, Y., 1974. The effect of risk on the investment in human capital. *Amer. Econ. Rev.* 64 (4), 950–963.
- March, J.G., Shapira, Z., 1987. Managerial perspectives on risk and risk taking. *Manage. Sci.* 33 (11), 1404–1418.
- Martins, P.S., 2021. Employee Training and Firm Performance: Evidence from ESF Grant Applications. Discussion Paper No. 14153, IZA.
- McDowall, A., Saunders, M.N., 2010. UK managers' conceptions of employee training and development. *J. Eur. Ind. Train.* 34 (7), 609–630.
- Mulders, J.O., van Dalen, H.P., Henkens, K., Schippers, J., 2014. How likely are employers to rehire older workers after mandatory retirement? A vignette study among managers. *De Econ.* 162 (4), 415–431.
- OECD, 2018. Good Jobs for All in a Changing World of Work. The OECD Jobs Strategy, OECD.
- Oosterbeek, H., 1996. A decomposition of training probabilities. *Appl. Econ.* 28 (7), 799–805.
- Pager, D., Quillian, L., 2005. Walking the talk? what employers say versus what they do. *Am. Sociol. Rev.* 70 (3), 355–380.
- Poullissen, D., Grip, A.D., Fouarge, D., Künn-Nelen, A., 2021. Employers' Willingness to Invest in the Training of Temporary Workers: A Discrete Choice Experiment. Discussion Paper No. 14395, IZA.
- Revelt, D., Train, K., 1998. Mixed logit with repeated choices: Households' choices of appliance efficiency level. *Rev. Econ. Stat.* 80 (4), 647–657.
- Sauermann, J., 2023. Worker reciprocity and the returns to training: Evidence from a field experiment. *J. Econ. Manag. Strategy* 32 (3), 543–557.
- Schivardi, F., Schmitz, T., 2020. The IT revolution and southern Europe's two lost decades. *J. Eur. Econom. Assoc.* 18 (5), 2441–2486.
- Schoar, A., Yeung, K., Zuo, L., 2023. The effect of managers on systematic risk. *Manage. Sci.*
- Schönfeld, G., Jansen, A., Wenzelmann, F., Pfeifer, H., 2016. Kosten Und Nutzen Der Dualen Ausbildung Aus Sicht Der Betriebe. Ergebnisse Der Fünften BIBB-Kosten-Nutzen-Erhebung. Bibb Report, BIBB, Bielefeld.
- Schönfeld, G., Wenzelmann, F., Pfeifer, H., Risius, P., Wehner, C., 2020. Ausbildung in Deutschland – Eine Investition Gegen Den Fachkräftemangel. Ergebnisse Der BIBB-Kosten-Nutzen-Erhebung 2017/18. Bibb Report 1/2020, BIBB.
- Sharma, S., Tarp, F., 2018. Does managerial personality matter? Evidence from firms in Vietnam. *J. Econ. Behav. Organ.* 150, 432–445.
- Shaw, K.L., 1996. An empirical analysis of risk aversion and income growth. *J. Labor Econ.* 14 (4), 626–653.
- Stevens, M., 1994a. An investment model for the supply of training by employers. *Econom. J.* 104 (424), 556–570.
- Stevens, M., 1994b. A theoretical model of on-the-job training with imperfect competition. *Oxf. Econ. Pap.* 46 (4), 437–562.
- Tannenbaum, S.I., 1997. Enhancing continuous learning: Diagnostic findings from multiple companies. *Hum. Resour. Manag.* 36 (4), 437–452.
- Train, K., 1999. Halton Sequence for Mixed Logit. Working Paper, Department of Economics, UC Berkeley.
- Train, K., 2009. Discrete Choice Methods with Simulation. Cambridge University Press.
- Train, K., Weeks, M., 2005. Discrete choice models in preference space and willingness-to-pay space. 6, pp. 1–16.
- Viscusi, W.K., 1980. Sex differences in worker quitting. *Rev. Econ. Stat.* 62 (3), 388–398.
- Williams, J.T., 1979. Uncertainty and the accumulation of human capital over the life cycle. *J. Bus.* 52 (4), 521–548.