Beyond Traditional Cost-Benefit Analyses of Vocational Education and Training - Workers' and Firms' Perspectives

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CHAPTER 1

Introduction

Rapid technological change and demographic trends tend to increase the demand for highly skilled workers. Human capital is the key competitive factor in the developed world and – as has been shown extensively – it is rewarded accordingly for both workers and firms. Similar to other types of investments, the decision to invest in human capital is the result of comparing costs and benefits. Most importantly, workers and firms are both involved in these investment decisions: firms are not only engaged in making continuing vocational training investments, but they are also major players in the formal education sector in countries with a dual education system.

Although the general importance of a highly skilled workforce is indisputable, a considerable number of people still refrain from participating in training. The aim of this dissertation is to provide an elaborate examination of cost-benefit analyses regarding vocational education and further training. Our empirical analyses are based on data from Switzerland and Germany, two countries in which vocational education is a fundamental element of the educational system.

As learning begets learning, and education may entail a strong degree of path dependency, the first part of this dissertation (chapter two) features an analysis of individuals who hold a tertiary educational degree and asks what paths they have taken to get there. Provided there exist not only straight educational paths, but also educational paths that combine both vocational and academic educations, we then examine how mixed paths compare to straight educational paths in terms of rates of return, a question that has not been studied before, to the best of our knowledge. To date, almost no research has been published regarding the labor market value of combining different types of education. The results of cost-benefit comparisons for people with tertiary degrees, however, might strongly depend on their path taken, i.e., vocational versus academic, or on the combination of the two. For instance, workers who first acquire a vocational education are, in general, still partly or even fully able

to participate in the labor market and earn reasonable levels of income when taking the next step. This fact substantially reduces these workers' opportunity costs. Academic education, on the other hand, is usually assumed to yield high returns due to considerable new knowledge, but this benefit is also associated with high opportunity costs while studying. Therefore, the first innovative contribution of this dissertation is the analysis of complete educational pathways and their respective cost-benefit structures. As a result we present new evidence indicating that combinations of different types of human capital (e.g., varying in their degree of work and labor market relations) are at least as competitive as straight educational paths. Therefore, the focus on the highest educational degree, frequently used in educational studies, can be misleading.

After focusing on the value of initial and formal education for labor market success, the second part of this dissertation (chapters three to five) examines continuing training. First, we are interested in discovering why considerable numbers of people do not undertake further training, even though further training seems to be associated with substantial returns for those who take part (chapter three). Again, we take account of training history (i.e., previous training decisions) and categorize non-participants into never-participants and temporary non-participants. The puzzle of training non-participation has been neglected in previous research. It may be that training participation would indeed have positive benefits for these people, but that the costs associated with participation are perceived as too high, resulting in an unfavorable cost-benefit ratio. But it may as well be a case of missing returns, e.g., non-participants would not have better prospects on the labor market or benefit from a reduced unemployment risk by participating. Even though the result is the same (i.e., non-participation in further training), it is still important to understand the reason why these people refrain from further training in order to identify means of increasing participation rates. Thus, the second innovative contribution of this dissertation lies in its analysis of the puzzle of non-participation in training, which simultaneously examines benefits and costs, as well as the training history of non-participants. We show that non-participants are not a homogenous group. They differ in several respects whereof the disregard of long term benefits, and related with it present-orientedness, is the one to be considered most significant for the explanation of never-participation.

Another aspect which has frequently been neglected in explaining training patterns is the fact that further training can involve two parties who have to take a positive decision to train. Training patterns are not only the result of workers' participation decisions, but also of firms' choices regarding the support of training. Firms' decisions might considerably affect workers'

training calculations. Thus, the next questions we raise concern firms' training decisions and their impact on workers' training participation rates. Theoretically, firms can be expected to share training costs, as well as some of the returns. As a first step, we empirically examine the costs associated with training participation (chapter four). Existing evidence demonstrates that employer-supported training is far more widespread than self-financed training. This indicates that firms play a prominent role in workers' training decisions. Employers have the choice to support their workers, either by covering monetary training costs or by providing training participation during work hours (i.e., by bearing part of the non-monetary costs). To date, however, various cost components (and, in particular, monetary and non-monetary costs) have not been examined separately in analyses of the training decisions of workers and firms. In order to identify the cause of non-participation, it is important to know whether these two cost components play different roles in training decisions. Therefore, we investigate the subsequent training decisions of workers and firms, focusing particularly on the relative roles of monetary and non-monetary costs. Thus, the third innovative contribution of this dissertation is its examination of the importance of various cost components for the joint training decisions of workers and firms. Our findings reveal the prominent role of non-monetary costs: the willingness of workers to sacrifice leisure time for training participation and the willingness of firms to provide training during working hours seem to be the main requirements for work-related training participations.

As a second step (chapter five), we completely take the firm-based perspective and study in more detail what kind of returns firms may get from engaging in training. There are a large number of studies (including chapter four of this dissertation) analyzing whether employers benefit from training through workers' increased productivity after participation. Although most of them find positive effects, these are sometimes small and sometimes not existent at all. Therefore, we examine whether there are additional returns to training, like returns stemming from a better reputation within the labor market as suggested by Sadowski (1980) but not empirically analyzed ever since. We expect that the existence of apprenticeship training and the provision of a systematic continuing training program will have indirect effects on productivity via improved recruitment success. Training may be one signal that is relevant to the quality of labor relations, which are otherwise unobservable to potential employees, but might be meaningful for their job decisions. We discuss and analyze the signaling character of firms' investments in human capital and we raise the question of whether these investments reduce the job vacancy rate and thereby improve firms competitiveness given tight labor markets. The provision of training (be it apprenticeship or

continuous training) has never been empirically studied with respect to its reputation effect. If training exerts a substantially positive recruitment effect, however, companies would not have the choice of either investing in training or poaching skilled workers from the external labor market. Rather, the only choice would be to invest in training and thereby increasing the chances of recruiting skilled workers. Thus, the major contribution of the fifth chapter is to identify reputation and recruitment effects of vocational training for firms. We find that besides the direct effect on the skill level of the current workforce, training effort of firms is also associated with a higher chance of recruiting highly qualified workers from the external labor market. Thus, the provision of training has – by treatment and selection of employees – a twofold effect on the average level of human capital in the workforce and is, therefore, influencing firms' competitiveness.

In the final chapter, we draw conclusions by synthesizing the results from the cost-benefit analyses of workers' and firms' investments in human capital, and we also present some preliminary policy implications.

CHAPTER 2

Risk-Return Trade-Offs to Different Educational Paths: Vocational, Academic and Mixed

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2.1. Introduction

Although it has been shown repeatedly that the type and highest level of education crucially determine an individual's labor market success, we know almost nothing about the labor market value of *combinations* of different types of education. On the one hand, there are individuals entering the labor market who have either taken a purely academic or a purely vocational educational path. On the other hand, we also observe a considerable number of individuals whose educational path includes a loop through both systems. Thus, it is neither adequate to include only the highest educational degree, nor is it adequate to ignore different types of paths an individual can take to receive his complete bundle of educational degrees and knowledge. In our study, we therefore compare the labor market value of different types of educational paths, and, in particular, we include mixed educational paths (i.e., combinations of both types of education). The question that primarily interests us is whether mixed educational paths are a detour or whether they are rewarded in the labor market. This is of particular importance given that, in many countries, the first educational decisions have to be made at a very early age, which may induce an interest or a need for corrections in later stages. Consequently, this is an especially important policy issue for countries with early educational tracking.

However, evidence on the labor market value of different types of educational paths in general and on the comparison of straight versus mixed educational paths in particular is virtually nonexistent. There is one exception of which we are aware[1]: Dearden et al. (2002) demonstrate that a purely academic curriculum is associated with a higher wage premium than a purely vocational curriculum. It should, however, be noted that, once the authors take into account the years of study, an educational path leading to higher-level vocational qualifications compares favorably to a purely academic curriculum.

To study the labor market value of different types of educational paths, we compare earnings. This allows us to analyze the labor market valuation of various combinations of qualifications and to find out if people who switch between the two sides of the educational system are rewarded for the additional qualification. In addition, we study lifetime net earnings of different educational paths because this is what is crucial for the individual educational decisions. Therefore, we consider not only the benefits but also the costs associated with each type of educational path. To compare which of the educational paths is most profitable, we calculate the internal rate of return, which is standard in traditional human capital literature. Since the internal rate of return is not beyond dispute in the finance or accounting literature, we alternatively calculate the Baldwin rate of return which is more standard in finance and accounting. This is one innovation of our study because, to the best of our knowledge, Baldwin rates of return have never been calculated for returns on education.

Finally, we also investigate whether different educational paths are characterized by different risk-return trade-offs. A few studies have already shown that individuals have to be compensated for risk associated with their educational decision (see, e.g., Hartog 2007; Hartog/Vijverberg 2007a). Some studies have analyzed the risk-return properties focusing on the level of general education (Palacios-Huerta 2003), on the level and field of education (Christiansen et al. 2007), or on labor market skills (Hartog/Vijverberg 2007b). However, the question of whether there are systematic differences in the risk-return trade-off of vocational and academic education or a combination thereof has not been analyzed. Since entrepreneurs are typically found to have a higher risk tolerance (e.g., Cramer et al. 2002; Ekelund et al. 2005; Caliendo et al. 2006), we additionally separate employees from entrepreneurs. The latter are often excluded from studies analyzing rates of return to education (because of difficulties attached to measuring earnings of self-employed persons). Hence, the knowledge

[1] Sociological research on complete educational paths concentrates on the impact of social inequality (e.g., see Hillmert/Jacob 2003) and is thus not within the scope of this study. Moreover, we explicitly focus on education and, thus, consciously abstract from life-long learning in this study. For the impact of the attainment of different qualifications (formal education or training) later in life see e.g., Conlon (2005).

concerning the relationship between education, professional status and earnings is very limited.

In our study, we start from the well-known human capital model in order to study the labor market outcomes of different types of educational paths, i.e. purely vocational, purely academic or mixed vocational and academic. We test our theoretical implications based on the Swiss Labor Force Survey (SLFS), which not only covers the whole educational path of an individual (which is a necessary prerequisite for our study) but also provides a broad enough spectrum of different types of educational paths in order to test the effect of differences in educational paths on labor market outcomes. We calculate the rate of return and the risk associated with different types of educational paths and find that mixed educational paths are well rewarded in the labor market.

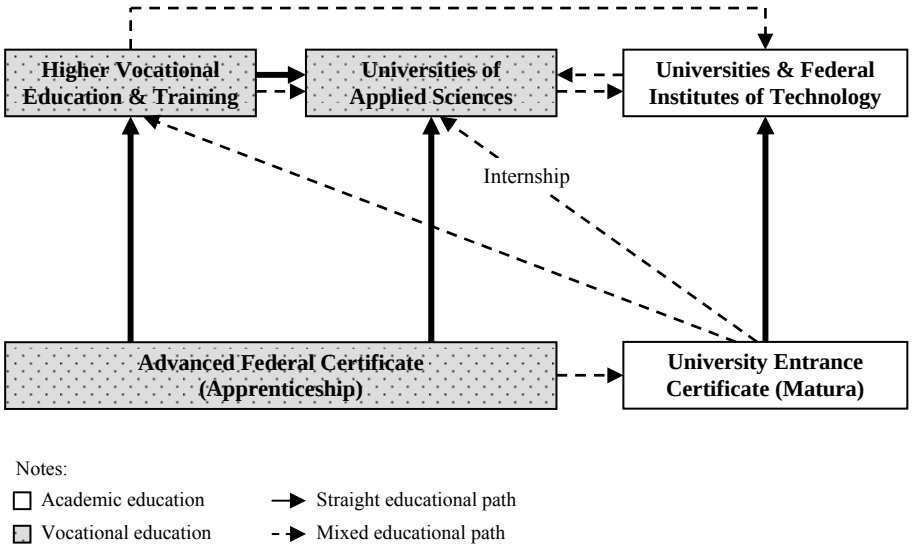
This chapter proceeds as follows: we first briefly describe the Swiss school system in order to characterize the different types of educational paths. In the subsequent sections, we present the main theoretical considerations and analyze empirically whether there are differences in the return to education that are consistent with our hypotheses. Moreover, we investigate the respective differences in the risk-return trade-off. The chapter finishes with a summary and some preliminary policy implications.

2.2. The Swiss schooling system

As in many countries, the school system in Switzerland consists of parallel branches of vocational and academic (school or college) education. Having completed nine years of compulsory school, two-thirds of a youth cohort choose to pursue vocational education and training (OPET 2007), mostly within the so-called dual system of apprenticeship training with an on-the-job training component and a theoretical component taught at respective vocational schools. They receive an "advanced federal certificate" after graduation. Afterwards, most of them work as skilled workers within their occupational fields at the companies where they were trained or in new companies. However, they also have several options to continue their education (cf. Figure 2.1, which gives a simplified diagram of the Swiss educational system[2]).

[2] A detailed description of the educational system in Switzerland can be found in Weber et al. (2001: 285-287).

Figure 2.1: Swiss educational system



They may choose to go into *higher vocational education* and attend a "higher vocational education and training school" or a "university of applied sciences".[3] In this case, they also end up with a tertiary educational degree that is as well recognized as other tertiary degrees in Switzerland. In our study we will call this the *purely vocational educational path*. On the other hand, students who finish an apprenticeship may also choose to switch to the academic side of the educational system. This will be denoted as a *mixed educational path,* with a university degree as the highest educational outcome.

Another option for students after compulsory education is staying in the school system by attending gymnasium and obtaining a "Matura" which grants them access to *higher academic education*, i.e., to all universities. We will call this the *purely academic educational path*. These students also have the option to switch to the vocational side of the educational system after they finished gymnasium, thereby combining academic and vocational education, denoted as a *mixed educational path*, but with a vocational tertiary degree as the highest educational outcome.

2.3. Theoretical analyses of different types of educational paths

As already pointed out by Becker (1964), investments in human capital improve skills and knowledge and thereby increase earnings. Since the skills acquired in different schools vary in terms of the level of specialization and diversification we expect the labor market outcome to

[3] Due to various changes in the sector of higher tertiary education, we will not distinguish between the two types of higher vocational education in the following sections.

depend on the type of education, namely, vocational or academic education, as well as on the level of education. We expect any additional qualification of either type to have additional returns on the labor market because they all increase productivity in various ways:

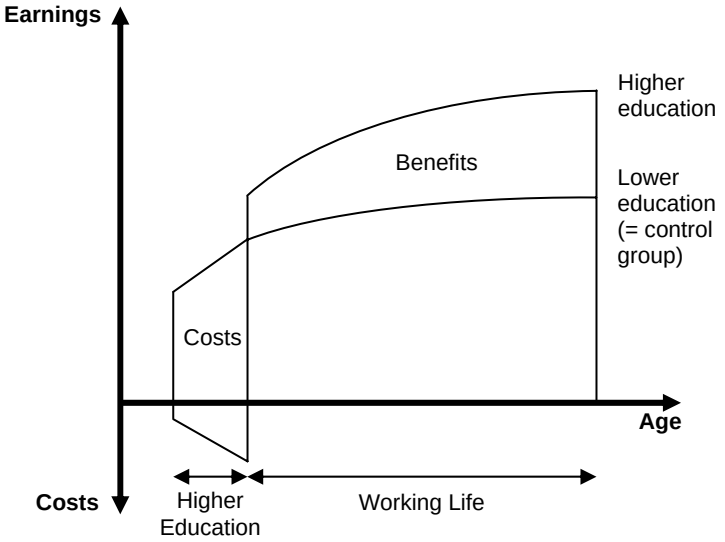
H1: Additional education of all types leads to higher earnings.

Thus, not only the highest level of education but complete educational paths matter for labor market outcomes. This sounds trivial but has never been studied due to the typical design of empirical studies.

However, for individual educational choices, we expect not only returns to be important but lifetime net earnings to be the crucial determinant. Therefore, we use the cost-benefit model presented in Psacharopoulos (1987, 1995) to consider costs and benefits associated with each type of educational path. Because we are interested in the private rates of return (as opposed to social rates of return), we focus on costs and benefits to the individual making the investment in human capital. The so-called opportunity costs comprise the major part of the total costs. Taking another educational degree typically leads to foregone earnings during that time. These are the costs we concentrate on although there are obviously also direct costs related to education, such as tuition fees. But compared to foregone earnings, direct costs in the Swiss educational system are substantially lower and for most educational degrees almost negligible.[4] While the costs of education arise during a short time period at the beginning, the benefits are expected over the whole life-cycle. The benefits consist mainly of the wage premium associated with having completed the next higher level of education (i.e., the difference between the earnings of more-educated individuals compared to a control group involving individuals with less education). As an example, Figure 2.2 shows the age-earnings profiles for individuals with higher education compared to those with the next lower level of education who are used as a control group.

[4] Although this statement might not be generally true, it certainly applies to Switzerland, where a substantial part of the educational costs are incurred by the state. This support, however, is not evenly distributed among the various types of education. For this reason we (all the same) consider direct costs.

Figure 2.2: The cost-benefit model



Source: Diagram modified from Psacharopoulos (1987, 1995).

In order to compare the profitability of different educational paths, our analysis relies on the approach presented by Psacharopoulos (1987): benefits and costs are discounted to a common point in time. The parameter of interest is the so-called internal rate of return, i.e., the discount rate at which the sum of discounted costs and the sum of discounted benefits exactly offset each other:

$$\sum_{t=k}^{T} \frac{(W_t^{HE} - W_t^{LE})}{(1+r)^t} = \sum_{t=0}^{k} \frac{(W_t^{LE} + C_t^{HE})}{(1+r)^t} \qquad (2.1)$$

where $(W^{HE}\text{-}W^{LE})$ is the wage premium for higher education *(HE)*, namely, the difference between the wage of those who completed higher education compared to the wage of those who did not pursue higher education after completion of lower education *(LE)*. This wage premium accrues from the time the higher education is completed $(t=k)$ until retirement (T). The right-hand side of equation (2.1) represents the direct costs C^{HE} as well as opportunity costs W^{LE}. Costs are incurred during completion of higher education (starting at $t=0$ and ending at $t=k$). As already noted, the parameter of interest is the rate r at which the sum of discounted benefits and the sum of discounted costs equalize. Thus, this internal rate of return indicates the profitability of an investment in education.[5] The higher the internal rate is, the more profitable is the investment.

This method of calculating the internal rate of return, although standard in traditional human capital literature, is not beyond dispute in the finance and accounting literature. One of the

[5] See Psacharopoulos (1987: 345) for a discussion why rate of return measures are typically used in cost-benefit studies (instead of calculating the net present value).

major criticisms concerning the internal rate of return measure is the implicit assumption that all returns can be reinvested at the rate of return being calculated for the initial investment (cf. e.g., Kierulff 2008).[6] This, however, does not have to be the case in reality. Since workers might hardly make the exact same investment again, but rather invest the returns in another project, using different rates of return might be more appropriate. In our context of human capital investments workers might only be able to invest in education at a specific time in life. After that they have to choose, at least partly, another form of investment, for example investments on the financial market that have a different rate of return. Therefore, we alternatively calculate the so-called Baldwin rate of return (Baldwin 1959): while benefits are compounded to the time of retirement such that the final value of an investment is calculated, costs are discounted to the starting point, i.e., the point at which we evaluate the profitability of an investment. It should be noted that one should use the rate at which the return to the human capital (i.e., earnings) could be reinvested. In a second step, we then calculate the Baldwin rate of return corresponding to the rate at which the discounted final value and the discounted investment equalize.

Two important facts about the educational system analyzed in this study must be mentioned: firstly, vocational education is usually associated with a lower full-time equivalent of study than academic education. Secondly, individuals who switch between the two sides of the educational system have to catch up on some "qualifications" (schooling or labor market experience) beforehand. Therefore, as soon as costs and benefits are considered, we expect educational paths with vocational education only to compare favorably to educational paths with academic education only; moreover, we expect that the profitability of mixed educational paths compared to straight educational paths is reduced.

Since human capital investments not only involve differences in average income and rates of return but also in income variance or risk, we are interested to see whether there is also a typical risk-return trade-off and whether these trade-offs differ depending on the educational path chosen.[7] Theoretically, one would expect higher income variance to be accompanied by higher average earnings, which prompts us to test the following hypothesis:

H2: Generally, the higher is the rate of return, the higher is the risk associated with a certain type of educational path.

[6] This, of course, can contrarily be seen as an advantage, because the internal rate of return can be calculated before knowing what the appropriate interest rate is.

[7] Besides, there is also the risk of dropping out of school and the risk of becoming unemployed (see e.g. Wolter/Weber 1999a; Wolter/Weber 1999b). The latter will be addressed in the empirical part of this chapter. Unfortunately, there is no information available about the risk of dropping out of school separately for individuals distinguished by educational path, and, thus, the risk of dropping out of school cannot be considered.

As entrepreneurs are typically assumed to have a higher risk tolerance than employees (see e.g., Kihlstrom/Laffont 1979) we expect the former to go for higher earnings by tolerating a higher level of risk. Therefore, it seems important to take account of these potential differences by distinguishing entrepreneurs from employees in our empirical analyses.

2.4. Methods to estimate returns and risks to different educational paths

To measure the rates of return and earnings risk to different educational paths, we first estimate a simple Mincer earnings function. Based on this estimation, we calculate internal rates of return and Baldwin rates of return for each educational path. As an alternative, we use a nonparametric estimation procedure. Finally, we calculate the risks associated with different educational paths and investigate the respective differences in the risk-return trade-off, and we additionally distinguish entrepreneurs from employees.

2.4.1. Empirical analysis of rates of return to different skill bundles

To study earnings differences of various types of educational paths, we include additional dummy variables (instead of using the continuous years of schooling variable) into the well-known earnings function of Mincer (1974). The basic equation we estimate can be written as:

$$\ln earnings = \alpha + \sum_i \beta_i \cdot educdum_i + \sum_{z=1}^{2} \chi_z \cdot \exp^z + \sum_i \sum_{z=1}^{2} \delta_{iz} \cdot educdum_i \cdot \exp^z + \varepsilon \quad (2.2)$$

We estimate an ordinary least square regression using the natural logarithm of earnings as the dependent variable and several dummy variables (*educdum*) indicating different educational paths (i.e., especially various mixed educational pathways) and a quadratic function of experience (*exp*) as the independent variables. In addition, we include interaction terms for education variables and experience as the experience-earnings profiles are assumed to vary by educational pathway.[8]

Equation (2.2) shows that our set of independent variables is strongly restricted to education and experience variables because including additional control variables (which are affected by the original educational decision) would result in biased estimates. Pereira/Martins (2001) show that including covariates representing post-educational decisions results in an underestimation of the impact of education on wages.

[8] The existence of different experience-earnings profiles by educational attainment has already been shown by Psacharopoulos/Layard (1979) and has recently been confirmed by Brunello/Comi (2004) for several European countries, including Switzerland.

With respect to the two potential biases typically discussed in connection with returns to education, i.e., ability bias and measurement error (Griliches 1977; Card 1999), they are not a problem in our analysis because we are only interested in the so-called treatment effect on the treated (i.e. the return of those who have chosen a certain educational path in comparison to those who have chosen a different educational path) and not in the treatment effect on the untreated (i.e. the return of a particular educational path to those who have actually chosen a different path).[9]

Since we are also interested in net returns, we cannot ignore that different educational paths differ in length and, as a result, in opportunity costs. Thus, we use the cost-benefit model presented in the previous section to calculate net rates of return. We start with estimating the above mentioned earnings function (2.2). In a second step, we then predict, based on the estimated coefficients, the age-earnings profiles for each educational path. In order to take into account opportunity costs, the earnings function is also estimated for individuals in the "control" group, i.e., those who stopped one step earlier in the respective educational path. Based on the estimated coefficients, we again predict age-earnings profiles for the control group. Following Psacharopoulos (1995: 8), we smooth out the age-earnings profiles by moving averages. In a third step, we calculate the internal rates of return (IRR) based on the adjusted age-earnings profiles for each educational path. The IRR is the discount rate at which the streams of future benefits and costs cancel each other out. This measure allows a direct comparison of the profitability of different educational strategies. Alternatively, we calculate the Baldwin rate of return (BRR) that corresponds to the rate at which the discounted final value and the discounted investments equalize.

Recently, the Mincer specification has come under criticism (see, e.g., Heckman et al. 2008).[10] It has been shown that the relationship between experience and earnings cannot simply be represented by a quadratic function (see, e.g., Murphy/Welch 1990). Therefore, we alternatively use a nonparametric estimation procedure: we perform separate estimations for each educational path using locally weighted regression (Cleveland 1979); in the specification that additionally considers the professional status, we perform separate estimations for each

[9] However, Dearden (1999) also shows that the two biases may cancel out each other: in their study the effect of omitted ability and family background completely canceled out the bias associated with measurement error and composition bias.

[10] Besides showing that it is important to allow the earnings-schooling-experience relationship to be estimated flexibly (by using nonparametric methods), the authors also raise concerns about other (strong) assumptions of the Mincer method, some of which we can consider: while we explicitly take into account that additional schooling years are associated with loss of working life and use net earnings, we do not have information about the psychic costs of education.

educational path. This procedure does not require the specification of a global function but smoothes the scatterplot of experience and earnings.

2.4.2. Empirical analysis of income risk to different types of educational paths

To measure the income risk of an education decision, Hartog/Vijverberg (2002) have derived various risk measures. We use the average squared coefficient of variance that measures the risk by the variations in relation to the respective level of income (because the same amount of variation has more severe consequences for small incomes than for large incomes). This risk measure is calculated as follows:

$$R_j = \frac{1}{N_j}\sum_{i=1}^{N_j}\left(\frac{Y_{ij} - \hat{Y}_{ij}}{\hat{Y}_{ij}}\right)^2 \qquad (2.3)$$

That is, it uses the average squared ratio of the standard deviation (true earnings (Y) minus predicted earnings ($\hat{Y}$)) to the predicted earnings ($\hat{Y}$).

As has been emphasized in the previous section, entrepreneurs and employees can be assumed to (strongly) differ in their degree of risk aversion. In order to separate the impact of such other factors, we additionally perform all the empirical analyses described above separately for entrepreneurs and employees (denoted as specification (2) in the following).

2.5. Data: the Swiss labor force survey (SLFS)

The Swiss Labor Force Survey has been conducted annually since 1991, and it includes a representative sample of Swiss households. The main idea is to collect information about individuals' working lives and the labor market in general. The SLFS is particularly suitable for answering the questions raised in this study. On the one hand, individuals' complete educational paths are reported in detail, and individuals are asked to report their current professional status. On the other hand, the data set provides information about various labor market outcomes such as yearly (net) earnings or unemployment risk. The analysis is based on the surveys from 1999 to 2005. It should be mentioned that the SLFS is a rotating panel and that, although the panel structure cannot be used in the present study[11], we have to control for the fact that people stay in the survey for several consecutive years. The fact that we use cross section data does not seem to be a disadvantage for our study: as has been shown by

[11] The fraction of people who can be identified before and after having completed some education is far too small to be used for an empirical analysis.

Schweri et al. (2008), individuals use contemporaneous market data to build their wage expectations.

The present study focuses on people who have completed higher tertiary education, be it vocational or academic.[12] We start by identifying the main educational paths leading to a tertiary educational degree. The most frequently used educational paths are presented in Table 2.1. To keep matters simple, we distinguish four groups of educational paths depending on whether the entrance was vocational or academic and whether the last educational step (the exit) was vocational or academic.

Table 2.1: Educational paths categorized by type and order of educational degrees

Entry \ Exit	Vocational	Academic
Vocational	**Typ I, purely vocational (64 %)** *Advanced Federal Certificate (Apprenticeship) + Higher Vocational Education & Training/ Universities of Applied Sciences*	**Typ II, mixed, with vocational entry (4 %)** *Advanced Federal Certificate (Apprenticeship) + University Entrance Certificate (Matura) + Universities & Federal Institutes of Technology* *Advanced Federal Certificate (Apprenticeship) + Higher Vocational Education & Training/ Universities of Applied Sciences + Universities & Federal Institutes of Technology*
Academic	**Typ III, mixed, with academic entry (9 %)** *University Entrance Certificate (Matura) + Higher Vocational Education & Training/ Universities of Applied Sciences* *University Entrance Certificate (Matura) + Universities & Federal Institutes of Technology + Higher Vocational Education & Training/ Universities of Applied Sciences*	**Typ IV, purely academic (23 %)** *University Entrance Certificate (Matura) + Universities & Federal Institutes of Technology*

Note: The percentages add to 100% and therefore solely refer to the sample of Swiss full-time employed males with one of the well-defined educational paths described above.

Although straight educational paths constitute the vast majority, mixed educational paths are not an unusual phenomenon: a considerable number of people combine academic and vocational qualifications. Among those with a higher tertiary education, more than 10% completed academic and vocational qualifications during their education (Typ II and III). This can be interpreted as a first indication of the permeability of the educational system. Approximately 12% of individuals who hold a higher vocational degree started with an academic education, and approximately 15% of individuals with an academic exit have started

[12] As there is no vocational equivalent to writing a dissertation after higher academic education, individuals with a doctoral degree are not included in our analyses.

with an initial vocational education. Interestingly, educational paths with repeated loops through both types of education are very rare and are thus not included in our analyses.[13]

In order to assess the labor market outcomes of various educational paths, we analyze net returns, more precisely, the level of earnings as well as the rates of return, for these four groups. Net incomes (compared to real incomes) are net of social security contributions but still represent income before taxes.[14]

In regards to the costs associated with a particular educational path, there are direct costs as well as opportunity costs. In order to correctly assign costs over an individual's life cycle it is important to acquire information that is as detailed as possible about the length of study, the direct costs per year of study and the age of entry into the labor market. Table A2.1 in the Appendix gives an overview over this information separately for each type of education and educational path respectively. As individuals in the SLFS are neither asked to report how long they have been studying nor about the expenses associated with their education we gather this information from two external sources: on the one hand, we assign an average length of study to each type of education based on data from the Swiss Federal Statistical Office. On the other hand, we rely on Weber (2003: 416) who provides several useful indicators concerning the Swiss educational system, among them one indicator representing the average private expenses associated with various types of education. Concerning the age at which an individual has completed his or her latest education, the SLFS provides valuable information: each individual in the survey is asked to report the year he or she has finished the latest education. In our empirical analyses the mode is used as the typical age of entry into the labor market in order to calculate average age-earnings profiles. As the vast majority of individuals retire at the age of 65 independent of their affiliation with one of the four educational groups and also independent of their professional status, we decided to use the same retirement age for the whole sample analyzed. Finally, we have to consider opportunity costs, which, in Switzerland, are by far the most important costs because there is basically no tuition for initial academic or vocational education (as both types of education are publicly funded or, in the case of an apprenticeship, provided by the companies free of charge). Thus, the profitability of an educational strategy depends crucially on opportunity costs, measured by earnings of

[13] This also holds true for the prevalent and extensively analyzed (see, e.g., Büchel/Hellberger 1995; Lewin et al. 1996) phenomenon of high school graduates completing an apprenticeship before starting university, which is well-known from Germany (a country with a similar education system).

[14] Zero earnings are always a potential indication of misreporting for which reason they are generally not included in our analyses. Nevertheless, this is only the case for 0.005% of the entrepreneurs and for none of the employees in the sample analyzed. Moreover, separately for each educational path and by professional status, observations with earnings above the 99th percentile or below the 1st percentile are dropped so that the results are not determined by outliers.

individuals who stopped one step earlier on their educational pathway. In order to ensure comparability individuals with a secondary educational degree in form of an advanced federal certificate (apprenticeship) – which represent the largest educational group – are used as control group for all educational paths leading to a tertiary educational degree. The estimation results underlying the calculation of the opportunity costs are presented in Table A2.2 in the Appendix.

Based on these data, we are now able to compare discounted benefits and discounted costs for each educational path. Basically, predicted age-earnings profiles should be adjusted for inflation and by unemployment rate. Since Switzerland has a comparatively low average unemployment rate, with around 3.5% in 2007, and individuals with tertiary education have a lower than average risk of unemployment (see Table A2.1 in the Appendix) we do not use additional adjustment here to simplify the analysis.[15] Concerning inflation of incomes we make an adjustment using the average annual long-term consumer price index for Switzerland which was 0.5%.[16]

For our analyses, we select Swiss[17] full-time employed males between 20 and 64 years of age. This leaves us with 10606 observations. We categorize individuals who report to be self-employed or employed at their own company as entrepreneurs. This applies to approximately 22% of persons analyzed in this study and hardly varies between the different educational paths. The average self-employment rate in Switzerland is about 14%, whereas individuals with a tertiary educational degree have a significantly higher probability (of about one-third) of being self-employed (BfS 2006). It should be noted that our definition of entrepreneur includes both those who employ workers and those who have no employees and just work for themselves. Unfortunately, we cannot separate these two groups in our analysis due to data restrictions. However, these differences within the group of entrepreneurs should be kept in mind when comparing the estimation results with those for employees. For the group of entrepreneurs without employees the fact that entrepreneurship holds fringe benefits as independence or flexibility of time consumption might be even more important than the resulting monetary earnings. For definitions and descriptive statistics of all the variables used see Table A2.3 in the Appendix.

[15] However, robust checks show – as expected – that our results are stable when considering unemployment risk.
[16] Detailed numbers are offered by the Swiss Federal Statistical Office. See http://www.bfs.admin.ch/bfs/portal/en/index.html.
[17] Including foreigners would not ensure comparability among the various educations completed.

2.6. Results: labor market outcomes to different educational paths

2.6.1. Estimating labor market outcomes and risk-return trade-offs

As described in section 2.4 we start with the estimation of an "extended" Mincer earnings function. The results are shown in Table 2.2 for specification (1) (according to equation (2.2)).

Table 2.2: "Extended" Mincer earnings function

Net yearly earnings	Spec. (1)
Purely academic	Reference
Mixed with vocational entry & academic exit	0.2793***
	(0.0488)
Purely vocational	-0.0060
	(0.0293)
Mixed with academic entry & vocational exit	0.1195**
	(0.0499)
Experience (exp)	0.0312***
	(0.0035)
Experience squared (expsq)	-0.0006***
	(0.0001)
Mixed with vocational entry & academic exit * exp	-0.0276***
	(0.0103)
Mixed with vocational entry & academic exit * expsq	0.0005
	(0.0004)
Purely vocational * exp	-0.0223***
	(0.0041)
Purely vocational * expsq	0.0005***
	(0.0001)
Mixed with academic entry & vocational exit * exp	-0.0158**
	(0.0071)
Mixed with academic entry & vocational exit * expsq	0.0003
	(0.0002)
Constant	11.2580***
	(0.0266)
Prob > F	0.0000
R^2	0.10
N	10606

Notes: The test for joint significance of separate experience profiles by educational path can be rejected. Cluster-robust std.errors are in parentheses. *Statistically significant at the 0.10 level; **at the 0.05 level; ***at the 0.01 level.

Source: Own calculations based on SLFS 1999-2005.

We find that, among all educational paths ending with a tertiary degree, the mixed educational paths are associated with the highest level of earnings: earnings of individuals with mixed educational paths are significantly higher than those of individuals with straight educational paths. For example, individuals with a mixed educational path with vocational entry earn a

32% earnings premium compared to individuals with a purely academic educational path.[18] The labor market obviously rewards the additional qualification(s) that individuals gather while switching between the two sides of the educational system. Thus, individuals who decide to change their initial educational path are not just taking a detour: they are rewarded by a higher income. The income premium compared to a purely academic educational path decreases over time, which supports the importance of our empirical model that allows the experience-earnings profiles to differ by educational paths. The results support hypothesis (*H1*), which states that additional qualifications – independent of whether they are of the same or of the other type – yield higher earnings. Our findings even indicate that there might exist some complementarities between the two types of education. However, a detailed analysis of this presumption is not within the scope of this study. Moreover, we interpret our results as evidence against the argument that switching between the two sides of the educational system only represents an adjustment of an initially false decision (e.g., individuals find out about their comparative advantage only later). If this were the case we would not expect such a high income premium attached to mixed educational paths.

Given the result from Table 2.2, there is still one puzzle to be solved: why are mixed educational paths, which have the highest earnings outcomes, chosen only by a minority of the workforce? We argue that the puzzle might be solved by taking into account the different costs associated with different types of educational paths. Therefore, we go one step further than the standard approach measuring labor market outcomes by Mincer earnings functions. We estimate and compare the internal rate of return and the Baldwin rate of return, respectively, for each educational path to account for different costs associated with different educational paths.

We calculate the rates of return based on Mincer earnings functions and alternatively based on earnings functions from a nonparametric approach. Results are given in Table 2.3.[19]

[18] Calculated as e^{β}, where β is the coefficient of the dummy variables indicating educational paths (see equation (2.2)).

[19] Detailed results of the calculation of the internal rates of return (IRR) and the Baldwin rates of return (BRR) are reported in Tables A2.4 and A2.5 in the appendix.

Table 2.3: Internal rates of return (IRR) and Baldwin rates of return (BRR) by educational path

	Spec. (1)			
	IRR		BRR	
	Based on Mincer earnings function	Based on non-parametric approach	Based on Mincer earnings function	Based on non-parametric approach
Purely academic (N=2412)	10.63%	10.03%	5.91%	5.79%
Mixed with vocational entry & academic exit (N=441)	8.01%	7.85%	4.74%	4.70%
Purely vocational (N=6842)	12.55%	12.01%	5.83%	5.77%
Mixed with academic entry & vocational exit (N=911)	19.38%	18.76%	6.97%	6.87%

Source: Own calculations based on SLFS 1999-2005.

We start by looking at the internal rates of return (IRR) and find that the picture is different from the one that we found by comparing incomes only after education is finished. As soon as lifetime earnings are considered, a purely vocational path compares very favorably to a purely academic path (due to a shorter duration in full-time education and a lower foregone income associated with a purely vocational path). These results are in line with Wolter/Weber (1999a), who report rates of return by highest educational degree for Switzerland. This might help to explain why, in Switzerland, the fraction of a youth cohort starting its non-compulsory education within the vocational system is quite stable over time and why it is on a very high level with two-thirds of the cohort. Regarding mixed educational paths, we find that educational paths with an academic entry and a vocational exit are still a more profitable choice than straight educational paths. Although individuals with these mixed educational paths also suffer from foregone income while they start their education in the full-time academic system, they do not suffer severely from foregone income in the second phase of vocational education. In this phase, they earn comparatively high incomes due to the academic education that they finished in the first stage of their education. Moreover, most of these individuals directly switch to the vocational side of the educational system right after their first academic education. In contrast, mixed educational paths with a vocational entry and an academic exit are the least favorable paths. The problem is that these educational paths mostly involve a change into full-time education in a later stage (i.e., after higher vocational education) in which individuals could have earned comparatively high incomes already. Thus, these individuals give up comparatively high potential earnings going back into full-time academic education in a second stage. Although the estimation results using a nonparametric approach are somewhat different from the ones using the extended Mincer earnings function, the general pattern remains the same.

Turning to the alternative measure of rates of return, the Baldwin rate of return, a relative comparison between the different types of educational paths confirms the results obtained by comparing internal rates of return, with the only difference being that BRR are about half the IRR. The latter is mainly due to our choice of a 3% interest rate for reinvestments, which is a realistic long-term interest for Switzerland. Since we are primarily interested in the relative profitability of various types of educational paths (and thus a comparison among the educational paths described above), it does not really matter in our analyses which profitability measure we use. However, for general policy issues, it might be more accurate to use the Baldwin rate of return to compare different types of investments.

In sum, as soon as costs and benefits are considered, purely vocational educational paths compare favorably to purely academic educational paths, and the profitability of mixed educational paths compared to straight educational path is reduced. However, there is still a puzzle to be solved: why do people choose educational paths with strongly unfavorable rates of return and why do not all choose the educational path with the highest return? We argue that, in addition to the average return to an educational path, one also has to look at the risks associated with different paths in order to conclusively solve the puzzle and better understand educational decision.

To study the risk-return trade-offs we calculate the income risk, measured as the earnings variation in relation to the respective level of income (see section 2.4.2), associated with each educational path. The risk measures are reported in Table 2.4.

Table 2.4: Income risk by educational path

	Spec. (1)	
	Based on Mincer earnings function	Based on non-parametric approach
Purely academic (N=2412)	0.14	0.15
Mixed with vocational entry & academic exit (N=441)	0.17	0.17
Purely vocational (N=6842)	0.13	0.13
Mixed with academic entry & vocational exit (N=911)	0.25	0.25

Source: Own calculations based on SLFS 1999-2005.

Generally, mixed educational paths are associated with a (substantially) higher income risk than straight educational paths and, thus, hypothesis (*H2)* cannot be confirmed. The exceptionally high risk attached to mixed educational paths with academic entry might be an important cause why these mixed educational paths are chosen only by a minority: there is a lot of uncertainty attached to taking a mixed educational path with academic entry. However,

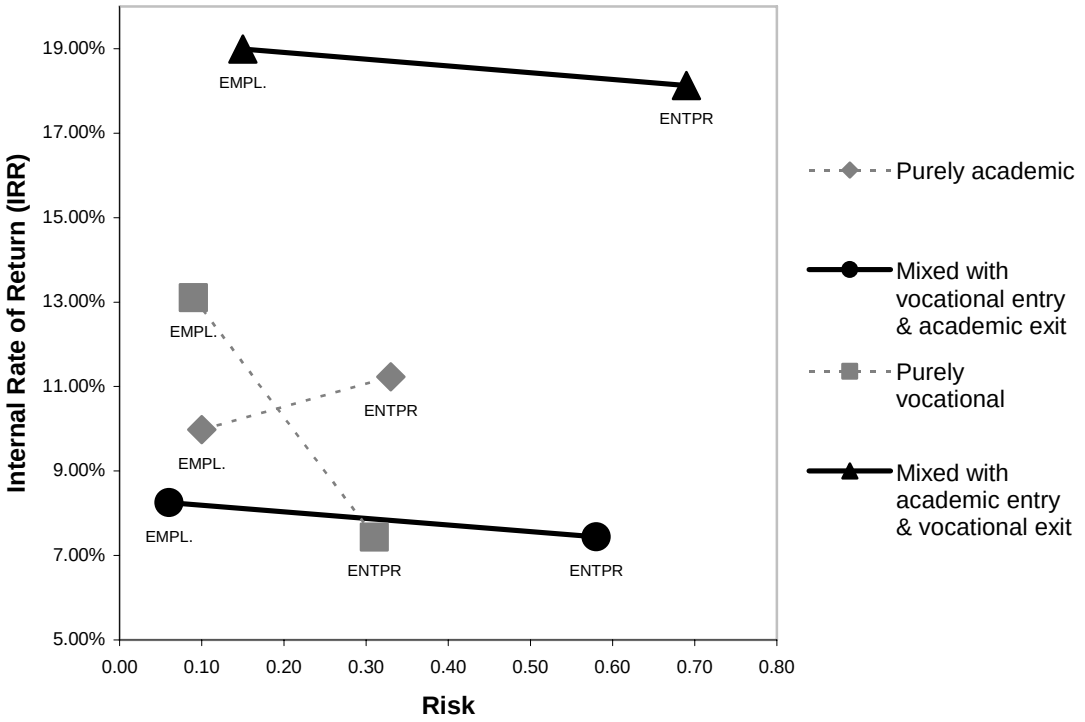
the picture still does not fully fit: why do some people choose a mixed educational path with vocational entry (i.e., the educational path with the lowest return and a high income risk)? As already mentioned before, we would expect entrepreneurs to differ from employees.

2.6.2. Estimating risk-return trade-offs for entrepreneurs and employees

To detect potential differences between entrepreneurs and employees we perform in the following all our analyses separately for the two groups. The estimation results of the extended Mincer earnings function are described in Table A2.6 in the Appendix. Similar to specification (1) we still find a significant positive impact on the level of earnings for combining academic and vocational education compared to choosing a straight educational path. The variables indicating entrepreneurship turn out to be insignificant with the exception of a variable representing entrepreneurs with a purely vocational educational background. Workers with a purely vocational educational path earn significantly less if they belong to the group of entrepreneurs than if they are employed.

The internal rates of return (IRR) and risk measures are displayed in Figure 2.3 (for detailed results see Table A2.7 in the Appendix).

Figure 2.3: Internal rate of return (IRR) and risk by educational path and professional status



Source: Own calculations based on SLFS 1999-2005.

For the interpretation of differences between entrepreneurs and employees, we focus on the estimation results based on the nonparametric approach: in this approach, we allow age-earnings profiles to be different for entrepreneurs and employees, which we think is necessary given the very different income-generating production functions. The assumption is supported by the fact that the internal rate of return results of the two estimation methods differ the most for entrepreneurs.

If we look at the structure of the results in terms of the internal rates of return (y-axis), we find an entrepreneurial premium for purely academic educational paths. In contrast, purely vocational educational paths have a higher internal rate of return for employees than for entrepreneurs. Hence, the skills acquired by taking a purely academic educational path seem to be a better prerequisite for entrepreneurship than those skills associated with a purely vocational educational path. As regards mixed educational paths there is also some evidence for lower average returns attached to entrepreneurship. However, the return differences between entrepreneurs and employees are very small and presumably even negligible. This indicates that switching between the two sides of the educational system does not restrict the occupational choice but rather extends it: mixed educational paths pay off both for entrepreneurs and employees.

But then, of course, the question arises why we observe employees or entrepreneurs in those educational paths that are not - at least in terms internal rates of return - the most favorable to them at all. Thus, there is still a puzzle that has to be resolved. We argue that, in addition to the average return to an educational path, one also has to look at the risks associated with different paths in order to solve the puzzle and better understand the educational decision in combination with the occupational choice.

If we now look at the four entrepreneurial markings in comparison to the four employee markings and concentrate on the axis indicating risk (x-axis), we find that employees in general are faced with a lower income risk than entrepreneurs. Within the group of employees there is some evidence for a risk-return trade-off: mixed educational paths with vocational entry have the lowest income risk providing a possible explanation why people with these educational paths accept the lowest rate of return. In contrast, mixed educational paths with academic entry have the highest rate of return but are also associated with the highest income risk. The numbers for straight educational paths lie in-between. However, although employees with purely vocational educational paths have higher average returns than employees with purely academic educational paths, they face (slightly) lower income risk. As regards the group of entrepreneurs we find that the income risk is twice as high for mixed educational

paths as for straight educational paths. Thus, combining both types of education does not reduce but rather substantially increases uncertainty about future incomes.

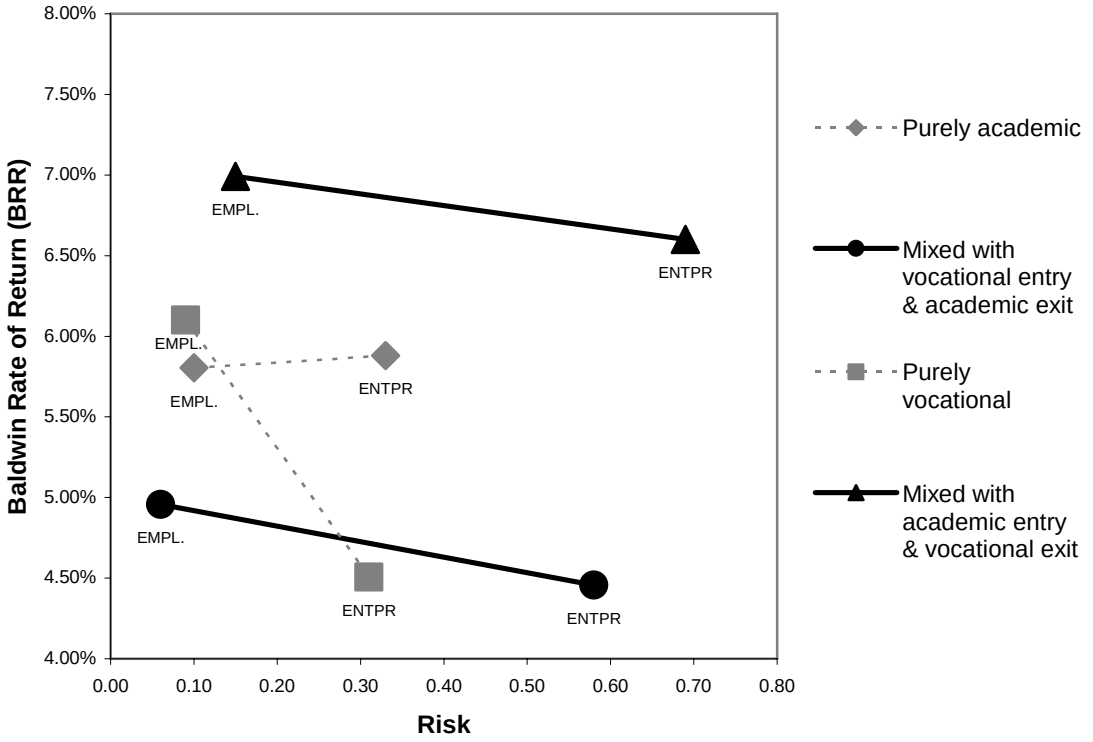
In summary, entrepreneurs face a considerable higher uncertainty about future income streams, which is on average not compensated by a higher rate of return, but rather the opposite is the case. The fact that entrepreneurs are less risk averse might not explain the sharp difference: in all educational groups (with the exception of purely academic educational paths) entrepreneurs accept a higher risk despite a slightly lower average income. Hence, entrepreneurs seem to benefit from other factors associated with entrepreneurship. For example Benz/Frey (2008) argue that they have a strong preference for being independent and being their own boss, which compensates them for the loss in income. This might especially hold for those entrepreneurs who have no employees. As already mentioned, the latter are assumed to have lower earnings than entrepreneurs with employees which could explain our results. Further research should possibly narrow the definition of entrepreneurs. This, however, would need new datasets with a larger number of entrepreneurs. Another explanation for the results could be that the differences are caused by measurement problems attached to earnings of entrepreneurs. On the one hand, in our data set earnings are measured by income before taxes. Income after taxes might be systematically different for entrepreneurs and employees. Due to higher tax reductions, the latter might pay fewer taxes and, thus, comparing net incomes we underestimate the returns for entrepreneurs. On the other hand, some individuals indicating to be self-employed might in fact be unemployed. As they fear a bad reputation they misreport their employment status. This then leads to a bias in our risk measure: leaving out this group of pretended self-employed persons the variance is expected to be considerable lower. Unfortunately, there is no possibility to identify such cases in our dataset. Thus, we have to keep in mind that workers might in fact have a better guess about their position in the income distribution than we as a researcher observe for each educational group, which may also explain why our results seem not rational at first sight.

Finally, in contrast with the other educational paths, entrepreneurs with academic entry have (slightly) higher average returns than employees; however, they also face a considerably higher income risk. The latter makes entrepreneurship obviously less attractive for individuals with high risk aversion so that highly risk-averse individuals decide to become employees and accept a lower income with a lower risk.

Alternatively, we can use Baldwin rates of return (BRR) instead of internal rates of return (IRR). This, however, does not change the main results, as can be seen in Figure 2.4.

Basically, the only differences are that BRR are about half the IRR (or even lower) and that the income gap between entrepreneurs and employees is increased.

Figure 2.4: Baldwin rate of return (BRR) and risk by educational path and professional status



Source: Own calculations based on SLFS 1999-2005.

Our findings provide evidence, that the occupational choice might be strongly related to the educational background. Lazear's jack-of-all-trades theory (Lazear 2005), which analyzes the occupational choice to become an entrepreneur as opposed to becoming an employee, might be useful in explaining the educational patterns that we find. The main argument is that, in order to be a successful entrepreneur, individuals have to be sufficiently skilled in a variety of areas, while persons who work for others should specialize and excel in one type of skill. Accordingly, the model predicts that the probability of becoming an entrepreneur is greater for individuals with more balanced skills. The question to be answered then is, who has a broad and who has a specialized educational background. We argue that persons who acquire vocational education are assumed to specialize in one type of skill and are therefore expected to be better off as employees than as entrepreneurs. In contrast, we think that mixed educational paths consist of a high variety of skills, as vocational and academic educations are combined. Thus, these educational paths are expected to be associated with a broad educational background, which is a good prerequisite for entrepreneurship. The same is true

for purely academic educational paths: academic education is assumed to be easily transferable to different types of occupations and job requirements. We do find some evidence for these propositions. However, this issue should be the focus of future research.

2.7. Conclusions

In this chapter we have examined the rates of return and the risks to complete educational paths with different combinations of academic and vocational education. We have distinguished a purely academic educational path from a purely vocational path and a mixed path with loops through both systems. Our results demonstrate that it is important to consider complete pathways instead of simply using the highest educational degree: the labor market rewards the additional qualifications that individuals gather while switching between the two sides of the educational system. Secondly, using the Baldwin rate of return instead of the internal rate of return substantially reduces the profitability of different educational paths. This, however, does not have an impact on the main conclusion in terms of a relative comparison among the various combinations of academic and vocational education. Thirdly, we find that analyses of rates of return to complete educational paths without additional consideration of income risk would be misleading, as individuals seem to care not only about rates of return but also about risk associated with a certain type of educational path. Finally, analyses of investments in human capital should distinguish entrepreneurs from employees.

Not surprisingly, the relative profitability of mixed educational paths is (substantially) reduced as soon as rates of return, instead of earnings, are compared. This might provide a possible explanation why mixed educational paths are chosen only by a minority. As already noted, the organization of the educational system could also be a cause for this phenomenon. In any case, it should be emphasized that complementarities between academic and vocational education seem to exist. Further research on mixed educational paths might provide an insight into the presumed relationship between the two types of education.

The importance of considering the fact that human capital investments involve differences not only in rates of return but also in income variance or risk, should not be underestimated. There is some evidence for risk-return trade-offs within the group of employees, but for entrepreneurs, this does not apply. Moreover, our findings indicate that the level of risk aversion is related to the occupational choice. Finally, uncertainty about future incomes might also play a role in educational decisions. Although this cannot be tested in our study, at least the results indicate the existence of such an effect: risk-averse individuals might not take mixed educational paths because these combinations of different types of educations are on

average associated with a high uncertainty about future income. The latter result is mainly driven by the group of entrepreneurs. Though, as concerns the group of entrepreneurs, the results should generally be interpreted with some caution given the difficulty of measuring entrepreneurial income after taxes and the differences between various types of entrepreneurs such as those who employ workers and those who just work for themselves. However different combinations of education within the group of mixed educational paths might anyway differ in terms of the usefulness of the bundle of skills acquired for entrepreneurial occupations and should possibly be distinguished in future research.

Finally, our analysis reveals implications not only for individuals' educational decisions but also for the organization of the educational system. Since our results indicate that mixed educational paths are a worthwhile strategy, the permeability of a national education system becomes an important aspect in its evaluation. This is a point of discussion that has been rightfully intensified since the Bologna-declaration[20]. We suppose that there might be some value to increasing the permeability of the educational system and especially to facilitating transitions between the two sides of the educational system. This would reduce the time loss associated with following a mixed educational pathway and might take the educational system a step forward towards an optimal allocation of students.

Considering the result that it is not just one (i.e., the highest) educational step, but rather the combination of educational experiences that matters for labor market outcomes, it might also be useful to analyze each further training participation as part of a complete training strategy. In the next chapter, we therefore differentiate training non-participants by their training history in order to study the puzzle of non-participation.

[20] See http://www.bmbf.de/pub/bologna_deu.pdf.

Appendix

Table A2.1: Overview over the information used for calculation of age-earnings profiles

	Unemployment rates[A]	Age at latest education completed[A]
Purely academic	1.71	26
Mixed with vocational entry & academic exit	1.01	29
Purely vocational	1.05	25
Mixed with academic entry & vocational exit	3.15	28
	Length of (full-time) study[B]	Direct costs
Advanced Federal Certificate (Apprenticeship)	3.5	-6000
University Entrance Certificate (Matura)	4	1200
Higher Vocational Education & Training	2	6500
Universities of Applied Sciences	3	2000
Universities & Federal Institute of Technology	4.5	2000

Note: The information for higher vocational education is composed of the numbers for Higher Vocational Education & Training and Universities of Applied Sciences.

Source: [A]Based on SLFS 1999-2005; [B]Weber (2003: 416); [C]Swiss Federal Statistical Office (http://www.bfs.admin.ch/bfs/portal/en/index.html)

Table A2.2: "Extended" Mincer earnings function for control group

Net yearly earnings	
Advanced Federal Certificate (Apprenticeship)	Reference
University Entrance Certificate	-0.0002 (0.0516)
Experience (exp)	0.0183*** (0.0011)
Experience squared (expsq)	-0.0003*** (0.0000)
University Entrance Certificate * exp	0.0104* (0.0057)
University Entrance Certificate * expsq	-0.0001 (0.0001)
Constant	10.8594*** (0.0101)
Prob > F	0.0000
R^2	0.09
N	16391

Notes: While the control group solely consists of individuals with an advanced federal certificate as highest educational degree, the estimation results for workers with a university entrance certificate are used to calculate the age-earnings profiles for individuals with an academic entry; *Statistically significant at the 0.10 level; **at the 0.05 level; ***at the 0.01 level.

Source: Own calculations based on SLFS 1999-2005.

Table A2.3: Definitions and descriptives of variables

Variable	Definition	Mean	(Std. Dev.)
Net yearly earnings	Net yearly earnings (log.)	95525.70	(36371.53)
Purely academic	1 if individual has taken a purely academic educational path (Typ IV, Table 2.1), 0 otherwise	0.2274	(0.4192)
Mixed with vocational entry & academic exit	1 if individual has taken a mixed educational path with vocational entry (Typ II, Table 2.1), 0 otherwise	0.0416	(0.1996)
Purely vocational	1 if individual has taken a purely vocational educational path (Typ I, Table 2.1), 0 otherwise	0.6451	(0.4785)
Mixed with academic entry & vocational exit	1 if individual has taken a mixed educational path with academic entry (Typ III, Table 2.1), 0 otherwise	0.0859	(0.2802)
Entrepreneur (entpr.)	1 if individual is self-employed or employed at the own company, 0 otherwise	0.2186	(0.4133)
Experience (exp)	Actual age minus age at graduation, measured in years	13.5395	(10.1530)

Source: Own calculations based on SLFS 1999-2005.

Table A2.4: Internal rates of return (IRR)

	Spec. (1): **IRR**			
	Based on Mincer earnings function		Based on non-parametric approach	
		& adjustment for inflation		& adjustment for inflation
Purely academic (N=2412)	10.07%	10.63%	9.48%	10.03%
Mixed with vocational entry & academic exit (N=441)	7.46%	8.01%	7.31%	7.85%
Purely vocational (N=6842)	11.98%	12.55%	11.44%	12.01%
Mixed with academic entry & vocational exit (N=911)	18.75%	19.38%	18.14%	18.76%

Source: Own calculations based on SLFS 1999-2005.

Table A2.5: Baldwin rates of return (BRR)

	Spec. (1): **BRR**			
	Based on Mincer earnings function		Based on non-parametric approach	
		& adjustment for inflation		& adjustment for inflation
Purely academic (N=2412)	5.66%	5.91%	5.54%	5.79%
Mixed with vocational entry & academic exit (N=441)	4.53%	4.74%	4.49%	4.70%
Purely vocational (N=6842)	5.61%	5.83%	5.54%	5.77%
Mixed with academic entry & vocational exit (N=911)	6.75%	6.97%	6.65%	6.87%

Source: Own calculations based on SLFS 1999-2005.

Table A2.6: "Extended" Mincer earnings function with distinction between entrepreneurs and employees

Net yearly earnings	Spec. (2)
Purely academic	Reference
Mixed with vocational entry & academic exit	0.2791***
	(0.0487)
Purely vocational	0.0071
	(0.0293)
Mixed with academic entry & vocational exit	0.1266**
	(0.0493)
Entrepreneur	-0.0181
	(0.0333)
Mixed with vocational entry & academic exit * entrepreneur	-0.0015
	(0.0932)
Purely vocational * entrepreneur	-0.1340***
	(0.0378)
Mixed with academic entry & vocational exit * entrepreneur	-0.0346
	(0.0689)
Experience (exp)	0.0315***
	(0.0035)
Experience squared (expsq)	-0.0006***
	(0.0001)
Mixed with vocational entry & academic exit * exp	-0.0276***
	(0.0103)
Mixed with vocational entry & academic exit * expsq	0.0005
	(0.0004)
Purely vocational * exp	-0.0200***
	(0.0040)
Purely vocational * expsq	0.0004***
	(0.0001)
Mixed with academic entry & vocational exit * exp	-0.0161**
	(0.0071)
Mixed with academic entry & vocational exit * expsq	0.0003
	(0.0002)
Constant	11.2592***
	(0.0267)
Prob > F	0.0000
R^2	0.12
N	10606

Notes: The test for joint significance of separate experience profiles by educational path can be rejected. Cluster-robust std.errors are in parentheses. *Statistically significant at the 0.10 level; **at the 0.05 level; ***at the 0.01 level.

Source: Own calculations based on SLFS 1999-2005.

Table A2.7: Internal rates of return, Baldwin rates of return and income risk by educational path and professional status

	Spec. (2)											
	Based on Mincer earnings function						Based on nonparametric approach					
	Employee			Entrepreneur			Employee			Entrepreneur		
	IRR	BRR	Risk	IRR	BRR	Risk	IRR	BRR	Risk	IRR	BRR	Risk
Purely academic (N= 1945, 467)	10.69%	5.93%	0.09	10.26%	5.81%	0.34	9.98%	5.80%	0.10	11.23%	5.88%	0.33
Mixed with vocational entry & academic exit (N= 348, 93)	8.10%	4.78%	0.07	7.68%	4.65%	0.58	8.25%	4.96%	0.06	7.44%	4.46%	0.58
Purely vocational (N= 5279, 1563)	13.92%	6.20%	0.09	6.59%	4.34%	0.32	13.11%	6.10%	0.09	7.43%	4.51%	0.31
Mixed with academic entry & vocational exit (N= 716, 195)	19.82%	7.05%	0.14	17.23%	6.67%	0.68	18.99%	6.99%	0.15	18.12%	6.60%	0.69

Note: N (number of observations employees, number of observations entrepreneurs).

Source: Own calculations based on SLFS 1999-2005.

CHAPTER 3

The Puzzle of Non-Participation in Continuing Training

An Empirical Study of Chronic vs. Temporary Non-Participation

in: *Zeitschrift für Arbeitsmarktforschung (ZAF), 40*(2/3), pp. 295-311 (2007) (with Uschi Backes-Gellner and Johannes Mure)

3.1. Introduction

Lifelong learning and continuing vocational training are becoming more and more important – a trend driven primarily by demographics and rapid technological change. On the one hand, the decline in birth rates and an aging workforce may cause a shortage of skilled labor, strengthening the importance of continuing vocational training (Bellmann 2003). On the other hand, technological change is strongly skill-biased, shifting labor demand toward more educated workers.[21] Employees with low levels of education run the risk of earning lower wages or, even worse, of being crowded out of the labor market because many jobs are disappearing (Spitz-Oener 2006). All this should cause a strong incentive to participate in continuing vocational training. Moreover, a large number of studies have shown that participation in continuing vocational training boosts individual wages.[22] Recent research has

[21] Chennells/Van Reenen (1999) survey the evidence on the correlation between technology and skills and come to the conclusion that the technological change is skill-biased.
[22] See Frazis/Loewenstein (2005) for US; Bassanini et al. (2005) and Pfeiffer (2000) for Europe.

also found non-monetary benefits, such as a reduced risk of becoming unemployed.[23] However, many individuals still refrain from participating in continuing vocational training. Even individuals who leave school with few or no qualifications, and whose only way to catch up would be to participate in continuing training, often decide not to participate in any continuing training measure (Schröder et al. 2004). Furthermore, Groot/Maassen van den Brink (2003) point to the existence of different training tracks, where workers not participating in further training in one year are likely to belong to the group of non-participants in the next year as well.

The question we raise in our study is how the puzzle can be solved, i.e. why is it that we find high returns to training for all participants on the one hand, and a large number of people not participating in training on the other hand. We argue that the solution is to be found in unobservable characteristics of two different groups of non-participants, namely temporary and chronic non-participants. This distinction has not been used before and the results are promising.

There is vast empirical literature devoted to estimating the (positive) impact of training, e.g. on the participants' wages, but only a few empirical papers analyze the rate of return that non-participants would have if they had taken part in continuing vocational training. Vignoles et al. (2004) analyze the effect of work-related training on wage growth, but focus only on middle-aged male workers. They estimate a selection model – taking into account that the training decision could be endogenous – and find substantial selection effects. Those workers who have received training measures gain substantial wage benefits, whereas non-participating workers would not have gained higher wages if they had participated. Groot (1995) analyzes the impact of an investment in firm-related training on wages and he finds that participants do have a positive rate of return. But the wage gain a non-participant would have received if he had participated is negative. Moreover, Leuven/Oosterbeek (2002) show that the return to work-related training is overestimated when self-selection is not taken into account. There is also similar evidence in the field of initial vocational training. Wolter et al. (2006) find that most of the apprenticeships in Switzerland generate net benefits for the participating firms. But they also show that if non-participating firms were to start training apprentices, they would incur significantly higher net costs compared to the participating firms, which follows from the fact that non-participants face much more unfavorable cost-benefit ratios. Thus, all these results indicate that due to the absence of sufficient benefits or due to higher costs, not participating in training could be a rational decision. But the question

[23] Büchel/Pannenberg (2004).

still remains as to the characteristics of those individuals for whom it may not pay to take part in training. It can be assumed that especially the distinction between different qualification levels is fundamental. Highly skilled workers seem to capture a larger share of the productivity effects of continuing training than low-skilled workers (Kuckulenz 2006), influencing the cost-benefit ratio of participation in further training.

Bassanini et al. (2005) studied the determinants driving the probability of receiving training and found that educational attainment and the skill-intensity of the occupation exert a positive impact. There seem to be complementarities between higher levels of education on the one hand and continuing training on the other. So individuals who are already disadvantaged in schooling and vocational education are more likely not to participate in lifelong learning later in life. Jenkins et al. (2003) found that the more qualified individuals are, the more likely they are to return to learning later in life. Moreover, the training probability decreases with age, and both part-time and temporary workers are less often found in the group of participants (Bassanini et al. 2005). In sum, training participants and non-participants differ in observable as well as in unobservable characteristics.

In addition, we argue in this study that non-participants cannot and also should not be treated as a homogeneous group. We distinguish between chronic and temporary non-participants for the first time and study their (potential) returns to continuing training separately. We are fortunate in being able to use a unique data set of non-participants with more than 1200 individuals.[24] This survey allows the distinction between individuals never taking part in training (chronic non-participants) and individuals currently not taking part, i.e. in the year of the survey (temporary non-participants). According to the character of the data set our study aims to study the differences between the two groups of non-participants and particularly to find out why some people never take part in continuing training. The structure of the chapter is as follows: the next section covers the theoretical framework, a simple cost-benefit model which mainly serves the purpose of structuring our empirical analysis and indicating important explanatory variables. Section 3.3 explains the econometric models and the estimation methods applied. The data set used is described in section 3.4. The results of the estimation of costs and benefits are presented in section 3.5, and conclusions are drawn in the last section.

[24] We thank the Expert Commission on Financing Lifelong Learning for collecting the data and for allowing us to use it.

3.2. Theoretical framework: the investment decision

To structure our empirical analysis of individual decisions to participate in training, we use standard human capital theory as a framework.[25] We assume that an individual's participation decision has to be seen as an investment decision. Individuals bear costs of participating in continuing training and in later periods expect various kinds of benefits in return. If discounted individual returns exceed individual costs, it pays to invest; otherwise it is rational not to invest in training (see e.g. Borjas 2005: 240ff. or Lazear 1998: 136ff.).[26] Or to be more precise, an individual only invests in continuing vocational training if the present value of his or her individual benefits exceeds the present value of his or her individual costs, i.e. if

$$\sum_{t=1}^{T} \frac{B_{ijt}}{(1+r)^t} \quad > \quad \sum_{t=1}^{t+z} \frac{C_{ijt}}{(1+r)^t} \qquad (3.1)$$

If inequation (3.1) does not hold, it would not be rational for individuals to invest in training. According to this model we expect chronic non-participants either to have higher costs and/or to have lower returns associated with participating in training than temporary non-participants. Higher costs could be due to lower ability, bad learning experience, or emotional distress triggered by schooling situations. Lower returns could be due to systematic differences in their workplaces, in motivation, in effort or career prospects.

The total costs (C) of an employee[27] (i) participating in training measure (j) in period *(t)* can be separated into direct costs and indirect or opportunity costs. Direct costs include participation fees, expenses for books, transportation costs or expenses for childcare, as well as non-monetary costs such as disliking learning or negative feelings attached to training due to bad past learning experience. Opportunity costs include either the forgone salary an individual could have earned if he had not taken part in continuing training (in the case of unpaid leave) or the loss of leisure. Some direct cost components (e.g. participation fees) may be the same for both chronic non-participants and temporary non-participants. Other cost components – especially non-monetary direct costs (such as learning stress) – may be substantially higher for chronic non-participants. Opportunity costs could also differ substantially but the overall effect is unclear ex ante. Compared to chronic non-participants,

[25] Becker (1975).
[26] Although in many cases the company may also bear some or even most of the costs of a training measure and therefore gets some of the returns, we only concentrate on the part of the costs that the individual bears and the parts of the returns that the individual receives. So if the company and the individual split costs and benefits, we would just have the individual's part in our empirical analysis.
[27] Full-time employees, part-time employees, unemployed persons, training participants as well as unemployed persons who would like to start working (again) in the next two years belong to this group.

temporary non-participants may be individuals with higher ability or motivation, they may learn more quickly and finish the same training measure in a shorter time. However, their forgone income per time unit may also be higher. At the same time, for individuals with lower income it might be more difficult to compensate for forgone earnings, so even lower absolute amounts of forgone income would still prevent them from participating, so the direction of the overall effect is theoretically not clear but remains an empirical question.

The benefits (*B*) also have two components: directly measurable benefits such as an increase in pay, and indirect benefits such as an increase in job security or long-term labor market prospects.

Furthermore, since the decision depends on the present value of costs and benefits, the remaining time in the labor market (*T*) and the individual discount rate play a crucial role. Individuals with a high discount rate *r* are more present-oriented. As a consequence they are less likely to accept costs today to gain benefits at some time in the future. This could for example be the case for chronic non-participants and would thus explain their non-participation. Taken together, the decision never to take part can occur either because chronic non-participants cannot afford the associated costs (monetary and/or non-monetary), because of low short-term benefits associated with training participation, or because of a high discount rate or a low remaining time in the labor market.[28] Since our cost and return data use only qualitative variables and are not in currency units (such as €) we cannot compute quantitative cost-benefit ratios. Therefore, we have to study costs and benefits separately in the following.

3.3. Estimation model and methods

In this section we present the estimation model for the costs that result from taking part in continuing vocational training as well as for various benefits that result from participation. In all our estimations we control for potential selection effects.

3.3.1. Costs

The basic equation we estimate can be written as:

$$\text{Costs} = \beta_0 + \beta_1 \cdot \text{VocTraining} + \beta_2 \cdot \text{ProfStatus} + \beta_3 \cdot \text{EmpCharacteristics} + \beta_4 \cdot \text{IndCharacteristics} + \delta \cdot X + u \qquad (3.2)$$

[28] Another potential reason causing a similar result could be that chronic non-participants lack necessary long-term information and thus cannot anticipate future benefits or possible job-offers correctly.

Since the dependent variable *costs* cannot be measured directly because our sample consists of non-participants only, we argue that we can use the individual's *willingness to pay* as a proxy providing us with a good lower bound for training costs. Since our non-participants all decided not to take part in training it seems reasonable to assume that the actual training costs were higher than their individual willingness to pay which is why they decided not to take part. Accordingly, *willingness to pay* provides us with the lower bound of actual training costs and can in this sense be used as a proxy for training costs.[29]

The independent variable "VocTraining" includes various dummy variables for vocational training measures, such as *apprenticeship*, *full-time vocational school*, *master craftsman* and *university*. Professional status, represented by "ProfStatus", includes variables indicating different categories such as *blue-collar worker*, *white-collar worker* and *self-employed* person.[30] "EmpCharacteristics" consists of variables describing the employment situation or workplace of the individual, including for example *number of employees* in the company or dummies such as *full-time employee*, *use a computer at work or at home* or *knowledge and skill needs change frequently*. Furthermore, we use individual control variables ("IndCharacteristics") such as *net income*, *age*, *gender* and having children (*kids) and* we control for industry-specific effects by adding industry dummies ("X"). In a second step, we add the *marital status* and *interaction terms* between the individual characteristics *gender* and *kids* as well as between *married* and *kids*. Findings from the German Socio-economic Panel (see Bellmann 2003) show that married women who live in a household with children are less likely to take part in continuing training whereas men in the same situation are more likely to participate. In a third step, we include a variable representing an individual's *time preference* and estimate the basic and the extended equation again. Controlling for present- or future-orientedness, it is possible to consider the impact of costs on the participation decision exclusively. For a full list of the variables included in the estimation models and the respective descriptive statistics see Table A3.1 (in the Appendix).

A major methodological problem is that the variable *costs* can only be observed for people who have at some time taken part in continuing vocational training. In our sample these are the temporary non-participants, who by definition must have taken part in training at some time in the past but not in the survey year (strictly speaking they are not only temporary non-

[29] Individuals had to specify the amounts they were willing to spend on continuing training out of five categories (in € p.a.). We use the upper limit per category as a proxy for the lower bound of actual training costs. See also section 3.4.

[30] We do not include civil servants because they are in a different situation as regards wages and job security. One could also consider excluding self-employed persons. But, as the results remain stable with or without this category, we decided not to do so in order to analyze a larger sample of non-participants.

participants but also temporary participants, which is what we make use of to estimate our cost variable). So for temporary (non-)participants we have (past) training costs, but for chronic non-participants such data obviously cannot be available. So we have a sample selection problem or an incidental truncation problem as it is called by Wooldridge (2003: 587–591). Whether we observe the (dependent) variable depends on the participation decision and it is therefore known for temporary (non-)participants only. It can be assumed that individuals are not randomly selected into the two groups[31], i.e. temporary (non-)participants presumably have systematically different costs than chronic non-participants (for example due to ability differences). Thus, an OLS regression of equation (3.2) produces inconsistent and biased estimates of the coefficients. The approach we use to solve this problem is as follows:[32]

First we model the probability of a person being a participant (participation equation):

$$y^*_{2i} = z'_i\gamma + u_{2i} \qquad \text{(latent variable } y^*_{2i}) \qquad (3.3)$$

where $u_{2i} \sim N(0, 1)$; we observe $y_{2i}=1$ (an individual took part in continuing vocational training) if $y^*_{2i} >0$. In this step we use the whole data set (temporary (non-)participants as well as chronic non-participants).

In the second step we examine y_{1i} and take into account that y_{1i} is only observed if $y_{2i}=1$ (outcome equation), meaning that in this step we can only include temporary (non-)participants:

$$y_{1i} = x'_i\beta + u_{1i} \qquad (3.4)$$

where $u_{1i} \sim N(0, \sigma^2_1)$ and y_{1i} is the costs associated with participation in continuing training. The error terms u_{1i} and u_{2i} are bivariate normal with correlation ρ. In our specification we follow Wooldridge (2003: 589), who strongly recommends that x is a strict subset of z and that there is at least one element of z that is not also in x (Wooldridge 2003: 589). Therefore, any explanatory variable in the regression equation should also be an explanatory variable in the selection equation. Moreover, we need at least one variable that affects selection but does not have a partial effect on y. The expected value of y_{1i} can then be written as:

$$E(y_{1i}|z'_i, y_{2i}=1) = x'_i\beta + \rho\lambda(z'_i\gamma) \qquad (3.5)$$

where $\lambda(z'_i\gamma)$ is the inverse Mills ratio (Wooldridge 2003: 588). If there is no correlation between the two equations ($\rho=0$), then the participation and outcome equations are independent and the OLS estimates of β would be unbiased. But if there is a correlation

[31] Leuven/Oosterbeek (2002).

[32] As the data set used does not have a panel structure, fixed effects estimation (Wooldridge 2003: 461-467; Wooldridge 2002: 265-279), which would also be a possible approach to take potential selection effects into account, cannot be used.

between the participation decision and the cost determinants, then there is an omitted variable problem, $\lambda(z'_i\gamma)$. That is why we first test whether there is a selection bias. If the null hypothesis ($\rho=0$) cannot be rejected, there is no selection problem and OLS estimations would be appropriate, otherwise selection effects have to be taken into account and the model explained above has to be used. To estimate such a model we can either choose the two-step estimation method recommended by Heckman (1976) or the maximum likelihood estimation recommended by Wooldridge (2003: 591). The latter is used in this study, as it is asymptotically unbiased, asymptotically normal and more efficient than the two-step estimator, provided that the appropriate assumptions are met (cf. Wooldridge 2003: 591, or Breen 1996: 40).[33]

3.3.2. Benefits

The following equation is used to assess the benefits associated with taking part in continuing training:

$$P(\text{Benefit}=1|x)=\Phi(\beta_0 + \beta_1 \cdot \text{VocTraining} + \beta_2 \cdot \text{ProfStatus} + \beta_3 \cdot \text{EmpCharacteristics} + \beta_4 \cdot \text{IndCharacteristics} + \delta \cdot X + u) \quad (3.6)$$

where *benefit* is a binary response variable. Due to data restrictions and in contrast to the cost analysis, we have to estimate the direct and indirect benefits of training in separate steps. First we use *increase in pay* as a dependent variable, indicating a direct benefit. To examine indirect benefits, we use *improving job security* as well as *improving employment outlook* as dependent variables. The independent variables are the same as in the cost equation and, as in the cost estimations, we have to solve the problem of unobserved heterogeneity. Individuals who have taken part in continuing vocational training may also be more motivated or may have different inherent skills and may therefore have higher earnings or better job prospects. Thus, the effect of participation would be overestimated. It is therefore important to use a maximum-likelihood probit estimation with selection instead of a simple probit estimation. The estimation procedure follows the same approach as that used in the case of incidental truncation with a metric dependent variable in section 3.1. The major difference is that there is a binary dependent variable. Therefore the outcome equation is as follows:

$$y^*_{1i} = x'_i\beta + u_{1i} \quad (3.7)$$

where $u_{1i} \sim N(0, 1)$ and $y_{1i}=1$ if $y^*_{1i}>0$.

[33] There are other studies preferring the two-step estimator, but there seems to be no common strategy (see Puhani 1997 for a survey of criticism of the different methods).

3.4. Data and descriptive statistics

Our empirical estimation is based on a unique data set commissioned by the German "Expert Commission on Financing Lifelong Learning". It covers individuals who did not participate in continuing training in the period from September 2001 to August 2002.[34] The data set contains information from computer-assisted telephone interviews with 1264 employees between 19 and 64 years of age and living in Germany. The sample is a representative sample of non-participants which resulted as a by-product of a survey of participants commissioned by the German Federal Institute for Vocational Education and Training (Bundesinstitut für Berufsbildung (BIBB)) for a separate project (cf. Beicht et al. 2006). Unfortunately, the participants' data were not available for this study, therefore our analysis is restricted to the non-participants sample as described in Schröder et al. (2004). Since our main interest lies in differences between chronic and temporary non-participants in training, we separate the respondents into those who have never participated in training[35] – referred to as chronic non-participants – and those who have taken part in continuing vocational training at least once in the past, but not during the survey period – referred to as temporary (non-)participants.[36]

Continuing training is defined very broadly in this study. It is any kind of further learning, be it formal, non-formal and/or informal learning or of a general or vocational nature, after the completion of initial vocational training (Timmermann et al. 2003: 55). Thus our training measure includes formal training programs that may take place in a company or at a continuing vocational training institute, it also includes informal on-the-job training (such as e.g. quality circles or job rotation) and even self-directed learning or conference participation.

The *training* variable is a dummy variable taking the value 1 if someone belongs to the temporary (non-)participants and 0 if someone is a chronic non-participant.[37] About one third of the people interviewed (419) belong to the latter category of chronic non-participants.

Regarding our dependent variables, people were asked about the costs and benefits associated with participation in continuing vocational training. (A full list of all variables and their

[34] For details of the survey see Schröder et al. (2004).

[35] We are aware that the period since entering the labor market and in which there is an opportunity of taking part in continuing vocational training is shorter for younger employees. But on the other hand, there is the inverse impact on the training probability of young and older workers caused by differences in the remaining time in the labour market. However, as we control for age, the estimated differences in costs and benefits should not be biased.

[36] Thus, we deliberately do not differentiate between the various further vocational training measures which the data set contains. Moreover, the duration of continuing vocational training might have an impact on returns (Budria/Pereira 2004). As we do not have duration data, we cannot make these differences. But for our main objective, analyzing why some people never take part in continuing vocational training, this is not crucial.

[37] If people had not participated during the period from September 2001 to August 2002, they were asked about participation in the past. Various types of training were specified and people had to answer for each type of training separately if they had taken part before the survey period. Thus, the risk of not remembering a participation and consequently being assigned to the chronic non-participants should be very small.

overall means and means broken down into temporary and chronic non-participants is given in Table A3.1). Descriptive statistics indicate that chronic non-participants rate the benefits associated with participation in continuing vocational training considerably lower than temporary (non-)participants. On average, chronic non-participants have a lower *willingness to pay* than temporary (non-)participants: the former are willing to invest about € 300, the latter more than € 500 on average, which we use as our proxy for training costs (because only the people in the latter group really know what they are talking about). The validity of the cost proxy that we obtain by this estimation is backed up by empirical results from the survey of participants given in Beicht et al. (2006). Based on data from actual participants they find that participants spend an average of € 502 on their training, which is astonishingly close to our proxy, i.e. the amount that temporary (non-)participants are willing to pay for continuing vocational training, which is € 520. With regard to our explanatory variables, we find that chronic non-participants are characterized by rather low or even no qualifications. For example, 20% of chronic non-participants but only 5% of temporary (non-)participants have no secondary school certificate. As a proxy for the discount rate we use the strength of an individual's preference for enjoying life and having enough time for personal interests and leisure. Descriptive statistics show that chronic non-participants are far more present-oriented than temporary (non-)participants, which indicates that present-orientedness could indeed have an influence on the individual training decision.

As explained in section 3.3, it is important to take selection effects into account. The equation determining the participation decision should contain a selection variable that satisfies two conditions. On the one hand the selection variable has to correlate with the participation decision. On the other hand it should not have an effect on the outcome of interest (the cost or benefit variables). Closely related to other empirical findings for Germany which use the number of children to identify the decision to take part in training because children put higher strains on the time budget (Büchel/Pannenberg 2004), we use the variable "taking part causes too much stress due to my job and private obligations" for the selection equation. Slightly less than half of the chronic non-participants (46%), but only a third of the temporary (non-)participants (35%) state that this was decisive for their non-participation, so the variable is correlated with the participation decision. In contrast, it is obvious that the stress a person expects due to job or family obligations is not related to the outcome variables such as direct training costs or marginal benefits resulting from a training measure. If we look at our estimation results, both assumptions are confirmed: the identification variable has a highly

significant impact on the probability of being a temporary (non-)participant (cf. section 3.5.3), but this is neither the case for costs nor for benefits.

After eliminating observations with missing data, a sample of 527 individuals is left for analysis.[38] Of these, 163 observations are censored and are therefore not included when estimating the outcome equation separately.[39]

3.5. Econometric results

3.5.1. Costs

Table A3.2 in the Appendix (model 1)[40] presents the results of estimating the basic equation. The selection model, using a maximum likelihood estimator, supports the view that there is selection into training based on unobservable characteristics: the hypothesis that there is no sample selection ($\rho=0$) is rejected at the 5% level. Thus, sample selection is a problem and the costs of training vary based on observable as well as unobservable characteristics. As can be seen, the selection effect is negative ($\rho= -0.1219$) which means that temporary (non-)participants have lower costs *ceteris paribus* than chronic non-participants, which is a highly plausible result. The unobserved characteristics that increase the likelihood of ever taking part in continuing vocational training are associated with lower actual expenditures.

Turning to the predicted costs[41], the result shown above is confirmed: on average chronic non-participants pay slightly more than temporary (non-)participants. The former have a predicted amount of about € 504, which is substantially higher than what the chronic non-participants are willing to pay (cf. section 3.4). A very important determinant seems to be vocational training: employees with an apprenticeship or a university degree or equivalent have significantly lower costs associated with training participation than employees without a secondary school certificate. Income does not have a significant impact on willingness to pay,

[38] The non-participants survey contains 1264 observations. As already explained, we do not include civil servants. Moreover, information about costs and benefits associated with training participation is not known for each non-participant. Finally, only interviewed persons for whom the vocational training, as well as specific individual and employment characteristics, are known can be included in the empirical analysis.

[39] Employees who did not choose one of the vocational training categories were generally excluded because they form a very small and heterogeneous group. Just a few people are family workers, employees subject to social insurance contributions or people who have not yet worked. They cannot be included because most of them have missing values in the other variables and with just one or two observations left, it is not possible to provide evidence.

[40] The tables only provide limited information about the selection equations. Full tables are available form the authors upon request.

[41] Predicted costs and benefits are estimated as follows: given the estimated coefficients of the outcome equation obtained by only including temporary non-participants but taking into account potential selection effects, we can plug in every non-participant in the regression. Thus, we obtain predicted costs as well as benefits for each of them.

so forgone salary does not seem to be crucial in the training decision. Therefore, the loss of leisure and the direct costs must be the major driving force. Individuals with the lowest level of schooling (no secondary school certificate) can be assumed to have the greatest difficulty in learning at school and might therefore also have a lower ability and less motivation to keep on learning later in their life because they would need much more time and effort than individuals with a higher qualification level. In addition, they are assumed to be much more averse to learning. Including a variable representing time preferences (model 2) does not yield a substantial change. The result shown above also holds for the models with additional individual characteristics and interaction terms (models 3 and 4). None of the added variables has an impact on the costs associated with continuing participation in training.

To summarize, individual training costs seem to play a major role in the individual participation decisions: the costs that chronic non-participants would have to bear are significantly higher than those actually borne by temporary (non-)participants.

3.5.2. Benefits

In our first estimation we use *increase in pay* as a dependent variable (Table A3.3 in the Appendix). Estimating the basic equation, the hypothesis that the outcome and participation equation can be estimated separately cannot be rejected ($\rho=0$). Therefore, we can use a simple probit model to estimate the outcome equation. The results are given in Table A3.3, models 1-2. We find that the significant variables generally take their expected signs: white-collar workers are more likely to have received an increase in pay than blue-collar workers, which is highly relevant since the latter are more likely to belong to the group of chronic non-participants. This is also true for employees holding a job characterized by frequent changes in knowledge and skill needs. Moreover, having children is associated with a lower likelihood of a wage increase. Calculating the marginal effects at the means of the independent variables shows that being a white-collar worker (compared to a blue-collar worker) is associated with a 9.1 percentage point higher likelihood of a pay increase, and the need for a frequent change of knowledge and skills with a 12.8 percentage point higher likelihood, while having children is associated with an 8.5 percentage point lower likelihood of an increase in pay. Moreover, having a master craftsman's diploma enters with a significant negative coefficient. They are less likely (9.1 percentage points) to have received a wage increase than someone without a secondary school leaving certificate. The results remain stable when the time preference variable is added (Table A3.3, models 3-4). Including the variables representing marital status (*married and single mother/father*) as well as interaction terms between *gender* and *children*

and between *marriage* and *children* yields almost the same results with the exception of the variable *kids*, which no longer has a significant impact (Table A3.3, last four models).
To summarize, the predicted probability of having received an increase in pay is about 15 percent: temporary (non-)participants have on average a higher and chronic non-participants a lower likelihood of receiving a pay rise. On the whole, the results are in line with those of Vignoles et al. (2004), who find that only those workers who actually participate in continuing training are able to realize wage gains. For those workers who did not participate in training, participation would not have been associated with a short-term wage gain in their current job.

Secondly, we consider the benefit of training in terms of job prospects. We first look at differences in *job security*. Again, we assume that individuals who occasionally take part in continuing training differ from those who never take part in training, which is supported by the results of the basic equation estimation. There is a positive selection effect of $\rho=0.8448$. The hypothesis that there is no sample selection ($\rho=0$) is rejected at the 5% level (Table A3.4 in the Appendix, models 1 and 2). Temporary (non-)participants are less likely to lose their jobs as a result of their inherent ability or other unobserved characteristics and not necessarily because of their participation in continuing vocational training. With respect to job security, being male, using a computer at work and working in a large company are associated with a lower likelihood of becoming unemployed. In calculating the marginal effects at the means of the independent variables we find that using a computer has a statistically and also an economically significant positive impact of 13.8 percentage points on the likelihood of increased job security. Bearing in mind that employees who use a computer at work are more likely to take part in continuing training than other workers, it can be assumed that it is particularly important for these people to keep on learning later in life in order not to lose their job. Being a male as compared to being a female increases the likelihood by 11.6 percentage points. Finally, firm size affects job security, but the effect is not practically large: if a firm grows by 1000 employees, the likelihood of participation in training increases by only 1.1 percentage points. On average the probability of increased job security is 21.4%, whereas the predicted probability for chronic non-participants is slightly lower and the probability for temporary (non-)participants is higher. The difference between the two groups is about 4%. Even after adding the variable representing present-orientedness, the above-mentioned results remain stable. The hypothesis that there is no sample selection can still be rejected, although only at the 10% level (Table A3.4, models 3 and 4). The variable does not

have a significant impact on job security, but – indirectly indicating a usually unobserved characteristic – reduces the influence of unobserved characteristics which usually make the coefficient of a separately estimated probit model biased. Nevertheless, estimating a selection model seems preferable. The last four models in Table A3.4 differ insofar as some variables indicating the marital status and interaction terms between *gender* and *kids* as well as between *marriage* and *kids* are added. This has an influence on the significance of some of the "Individual Characteristics" variables, which are worth looking at: the likelihood of an increase in job security falls with increasing age but at a diminishing rate. The most notable result is the significant positive coefficient of having children. The marginal effect is very high – at 36.5 percentage points (and 39.2 percentage points respectively). Turning to the added variables, we find that being married has a significant and positive impact on job security (21.8 and 22.7 percentage points respectively). But if a married couple has children, the likelihood of having a secure job is reduced by 30.9 (and 32.7) percentage points. Bearing in mind that the coefficient of the variable *kids* is also very high, families with children are still less likely to lose their jobs.

Turning to *prospects on the labor market*, we find that a separate estimation of the outcome equation does not yield biased estimates of the coefficients: the hypothesis that there is no sample selection ($\rho=0$) cannot be rejected at the 10% level irrespective of the included explanatory variables. As the regressions of the models including marital status and the interaction terms have a higher significance, we turn to the second part of Table A3.5 (in the Appendix). In particular, the coefficients of the variables *married* and *married with kids* are highly significant. While being married has a positive effect on the likelihood of increased prospects on the labor market, having children in addition has a significant negative impact; taking into account the coefficient of *kids*, which is positive but not significant, it is no longer clear whether there is really a difference between married couples with and without children. Interestingly, working full-time, which has neither an influence on costs nor on the likelihood of an increase in pay or job security, has a significantly positive effect. Working full-time instead of part-time (or other forms) is associated with a marginal effect of 16.9 percentage points. As with job security, firm size enters with a positive and significant coefficient with an effect that is not practically large. The predicted probability of continuing training as a necessary condition for increased prospects on the labor market is 48.5% for temporary (non-)participants and 47.7% for chronic non-participants. Almost half of each group benefits from participation in continuing vocational training as far as increased prospects on the labor

market are concerned. Therefore, this seems to be a highly important and non-negligible factor.

To summarize, chronic non-participants would not gain as much as temporary (non-)participants in terms of increased job security. Chronic non-participants are more likely to be found in unskilled jobs. Therefore, they are most likely not faced with constantly increasing requirements at the workplace due to technological change, but with the situation that their job may disappear. Thus, considering only their current job, the decision not to take part in training seems to be a rational decision in the short and medium term because chronic non-participants would indeed not gain much in their current job – and they know it. However, since it is precisely these workers who are at a higher risk of losing their jobs[42] it would be important for them to think more in the long term. As we have seen, continuing vocational training would be necessary to improve their employment outlook. Participation in training could provide them with knowledge enabling them to do more complex or even completely different work, which in turn would make it easier to find new jobs once they lose their current jobs. Thus, information asymmetries seem to play a crucial role: chronic non-participants would benefit as much as temporary (non-)participants in terms of employment outlook, but do not seem to realize that in addition to returns associated with their current jobs (where returns are indeed very low) participation in training could also lead to better prospects on the labor market and could therefore help them to find new jobs if they are laid off.

Our hypothesis on benefits is therefore only partly confirmed. Chronic non-participants would indeed have lower benefits regarding their current jobs,[43] but they would still benefit as much as temporary (non-)participants in terms of long-term labor market prospects. Another important result is that chronic and temporary non-participants have to be distinguished in empirical studies because they are rather different in their costs and benefits. Therefore, studies that do not differentiate between chronic and temporary non-participation underestimate the returns to education for temporary (non-)participants on the one hand and on the other hand overestimate the returns to education for chronic non-participants. So if, for example, these two groups are not differentiated, results on returns to training cannot be expected to be reliable.

[42] Almost one in five unskilled workers was unemployed in Germany in 2003 (iwd 2006).
[43] This result corresponds with Groot's (1995) finding that non-participants would have a negative wage gain in the case of participation.

3.5.3. Participation decision

Given the above results it seems important to distinguish between chronic and temporary non-participants because they are faced with a significantly different cost-benefit structure of training. Accordingly, the question is what distinguishes the two non-participation groups. Table A3.6 (in the Appendix) provides probit regression results concerning the probability of taking part in continuing vocational training. The first two models of the Table give results for the basic equation (model 1) and for the basic equation with a variable representing time preference added (model 2); the last two models provide both models with some more individual characteristics. The following results are similar in all of the models. The likelihood of taking part in continuing vocational training is significantly higher for a master craftsman, a worker who has completed an apprenticeship or who holds a university degree or equivalent than for a worker without a secondary school certificate. The results are consistent with those reported in the literature: Bassanini et al. (2005), for example, find that having a lower level of education exerts a negative impact on the probability of training participation. Surprisingly, there is no significant distinction between different professional statuses. The need for changing knowledge and skills as well as the use of a computer significantly increases the likelihood of being a temporary (non-)participant rather than a chronic non-participant. As expected, the likelihood of being a chronic non-participant is significantly higher for employees who consider training to be too much stress in addition to their jobs and private obligations. The regressions with the variable representing time preferences indicate that orientation towards the present (high discount rate) is negatively associated with the likelihood of being a participant. Individuals with a high discount rate obviously invest only if they can expect an immediate gain. Entering variables indicating marital status and interaction terms between different individual characteristics leads to the following: contrary to the results usually found in the literature (see e.g. Bassanini et al. 2005), people who are employed full-time are significantly less likely to belong to the group of temporary (non-)participants. Single mothers/fathers as well as people who are married (no matter whether they have children or not) are more likely to take part in continuing vocational training. There is no significant difference between mothers and fathers

3.6. Conclusions

Although continuing training is becoming increasingly important, a large proportion of the workforce surprisingly does not participate in training. This seems particularly puzzling since

a large number of studies demonstrate that participation in training leads to substantial positive returns. In our study we show that non-participants are not a homogeneous group and that the distinction between chronic non-participants and temporary (non-)participants is fundamental to solving the puzzle. We compare chronic non-participants with temporary (non-)participants (employees who have taken part in continuing training at least once in the past but are not currently participating). We assume that the two groups differ in observable as well as unobservable characteristics and use selection models in our empirical analysis in order to account for this problem. We study differences in the costs, benefits and/or discount rates of the two groups of non-participants. We find that individuals who are chronic non-participants would have to bear higher costs if they were to participate. Moreover, the benefits associated with their current job would be lower, i.e. any pay increases or reduction in unemployment risk would be smaller for chronic non-participants than for temporary (non-)participants. However, the results indicate that in the long run chronic non-participants would benefit from participation in terms of improved prospects on the labor market, which indicates that the discount rate of chronic non-participants is probably exceptionally high. Although participation in training would not protect those people from losing their jobs, it would increase their likelihood of finding new jobs once they have become unemployed, but this may seem to be too far in the future to be important at the present time. Angrist/Lavy (2004) argue similarly with respect to investments in schooling by low-achieving students and suggest using short-term financial rewards to reduce the problem of exceptionally high discount rates. Based on a randomized trial, they present evidence that financial incentives do indeed increase high school certification rates.

Another potential reason could be that chronic non-participants lack the necessary information and can therefore not anticipate future benefits or possible job-offers correctly. Thus, when thinking about policy implications it seems necessary to increase workers' awareness of returns that are not directly associated with their current job, but which might lie far in the future and which might therefore often be neglected. Small financial incentives attached to completing training measures could be an option with which to overcome the problem of exceptionally high discount rates.

Even if (chronic) non-participants are aware of the importance of continuing vocational training, its high costs might still prove an obstacle to participation. Certainly total costs

critically depend on whether the worker receives employer support. Hence, in the next chapter, we investigate the joint training decisions of workers and firms.

Appendix

Table A3.1: List of variables used

Variable	Notes	**Total**	**Temporary**	**Chronic**
		Mean (Std. dev.)	Mean (Std. dev.)	Mean (Std. dev.)
Participation in continuing vocational training	Dummy = 1 if a person is a temporary (non-)participant, otherwise 0	0.6647 (0.4723)		
Willingness to pay	Willingness to pay in €	449.2002 (978.3869)	519.3101 (1040.6510)	309.8956 (824.8570)
Increase in pay	Dummy = 1 if a person received an increase in pay, otherwise 0	0.1593 (0.3661)	0.1618 (0.3686)	0.1538 (0.3615)
Job security	Dummy = 1 if continuing vocational training is necessary to improve job security, otherwise 0	0.3608 (0.4804)	0.3753 (0.4845)	0.3316 (0.4714)
Prospects on the labor market	Dummy = 1 if continuing vocational training is necessary to improve prospects on the labor market, otherwise 0	0.4939 (0.5002)	0.5286 (0.4995)	0.4253 (0.4950)
Independent variables				
Without secondary school certificate	Reference	0.0951 (0.2934)	0.0536 (0.2254)	0.1772 (0.3823)
Apprenticeship	Several years of vocational training in school and on the job	0.7207 (0.4488)	0.7407 (0.4385)	0.6810 (0.4667)
Full-time vocational school	Several years of vocational training in school	0.1621 (0.3687)	0.1686 (0.3746)	0.1494 (0.3569)
Master craftsman		0.0501 (0.2182)	0.0664 (0.2492)	0.0177 (0.1321)
University of applied sciences		0.0280 (0.1651)	0.0370 (0.1890)	0.0101 (0.1002)
University		0.0475 (0.2129)	0.0600 (0.2377)	0.0228 (0.1494)
Blue-collar worker	Reference	0.3744 (0.4842)	0.3193 (0.4665)	0.4835 (0.5004)
White-collar worker		0.5586 (0.4968)	0.6066 (0.4888)	0.4633 (0.4993)
Self-employed person		0.0671 (0.2502)	0.0741 (0.2621)	0.0532 (0.2246)

Full-time employee	Dummy = 1 if a person is employed full-time, otherwise 0	0.5509 (0.4976)	0.5581 (0.4969)	0.5367 (0.4993)
Change	Dummy = 1 if knowledge and skill needs change, otherwise 0	0.5035 (0.5002)	0.5352 (0.4991)	0.4400 (0.4971)
Meeting the needs	Dummy = 1 if knowledge and skills meet the needs, otherwise 0	0.8239 (0.3810)	0.8346 (0.3718)	0.8026 (0.3986)
Computer private	Dummy = 1 if a person uses a computer privately, otherwise 0	0.6916 (0.4620)	0.7663 (0.4235)	0.5431 (0.4988)
Computer at work	Dummy = 1 if a person uses a computer at work, otherwise 0	0.5899 (0.4921)	0.7048 (0.4565)	0.3631 (0.4816)
Number of employees		1744.6100 (3470.5110)	1936.5700 (3634.3540)	1342.0280 (3064.8140)
Age		40.7342 (10.1024)	41.0051 (9.7997)	40.1964 (10.6704)
Age squared		1761.2450 (840.6438)	1777.3320 (825.8251)	1729.3190 (869.4981)
Sex	Dummy = 1 if a person is male, otherwise 0	0.4440 (0.4971)	0.4674 (0.4993)	0.3975 (0.4900)
Kids	Dummy = 1 if a person has at least one child, otherwise 0	0.5686 (0.4955)	0.5755 (0.4947)	0.5552 (0.4977)
Net income	Net income in €	1319.3630 (1151.1690)	1412.6960 (1259.7100)	1140.6910 (882.3360)
Married	Dummy = 1 if a person is married, otherwise 0	0.6746 (0.4687)	0.6918 (0.4620)	0.6405 (0.4805)
Single mother/father	Dummy = 1 if a person is a single mother/father, otherwise 0	0.0850 (0.2789)	0.0793 (0.2704)	0.0962 (0.2952)
Present-oriented	Dummy = 1 if enjoying life and having enough time for personal interests/leisure is a very important aim in life, otherwise 0	0.3422 (0.4746)	0.3252 (0.4687)	0.3756 (0.4849)
Strain	Dummy = 1 if continuing vocational training is too much strain besides job and private obligations, otherwise 0	0.3888 (0.4877)	0.3514 (0.4777)	0.4639 (0.4993)

Table A3.2: Costs

	Basic equation	**… & time preference**	**… & interaction terms**	**… & time preference, interaction terms**
	MLE model 1	MLE model 2	MLE model 3	MLE model 4
OUTCOME EQUATION: costs				
Vocational training				
Apprenticeship	-284.9283*	-283.9043*	-283.4516*	-282.5839*
	(152.7667)	(153.1549)	(153.5701)	(153.9265)
Full-time vocational school	45.7697	48.5427	63.9263	66.3883
	(153.5818)	(153.4299)	(155.8915)	(155.8606)
Master craftsman	184.8608	196.9994	174.8389	186.0187
	(214.6432)	(216.5999)	(224.8583)	(226.3103)
University of applied sciences	-279.7773*	-283.0289*	-292.7146*	-297.5709*
	(151.5675)	(150.7788)	(155.9092)	(155.7774)
University	-271.0859**	-260.1087*	-283.5607**	-272.3519*
	(135.8782)	(135.1057)	(140.0331)	(139.2009)
Professional status				
White-collar worker	64.1820	64.6401	52.0351	52.3419
	(106.5599)	(106.5510)	(106.4128)	(106.3334)
Self-employed person	348.3002	366.4148	338.2618	355.9353
	(258.4311)	(259.1558)	(261.7224)	(262.0150)
Employment characteristics				
Full-time employee	34.3136	42.8373	46.0780	55.3230
	(105.8100)	(109.9947)	(118.6091)	(122.6371)
Change	-14.8042	-22.9363	-8.9708	-16.9396
	(87.6586)	(89.4323)	(89.1424)	(90.7878)
Meeting the needs	55.0591	56.1919	55.3781	56.8354
	(148.1695)	(146.7103)	(150.0058)	(148.4188)
Computer private	34.7630	27.2637	42.5436	35.2355
	(92.1616)	(93.1956)	(94.6205)	(95.2035)
Computer at work	129.8048	133.1337	126.4736	129.7036
	(82.4911)	(83.7198)	(82.1286)	(83.4052)
Number of employees	-0.0115	-0.0107	-0.0106	-0.0097
	(0.0100)	(0.0099)	(0.0102)	(0.0101)
Individual characteristics				
Age	16.8039	15.5175	12.7199	11.3838
	(25.9540)	(25.7850)	(25.5104)	(25.4447)
Age squared	-0.3272	-0.3125	-0.2836	-0.2686
	(0.3209)	(0.3180)	(0.3115)	(0.3096)
Sex	-117.8094	-128.1258	-130.4606	-138.2807
	(135.9695)	(134.9939)	(154.3147)	(152.8725)
Kids	-110.2118	-102.8876	-19.4856	2.7676
	(101.0877)	(100.8610)	(153.4032)	(156.6122)
Net income	0.0130	0.0135	0.0128	0.0134
	(0.0279)	(0.0278)	(0.0291)	(0.0291)
Married			119.0190	121.9026
			(148.2023)	(148.3600)
Single mother/father			-69.3903	-75.6189
			(157.4123)	(159.3330)
Male & kids			5.1082	-0.4381
			(178.9591)	(179.0223)
Married & kids			-98.7678	-112.1637
			(149.4645)	(153.2088)

Time preference				
Present-oriented		91.4999 (95.8714)		92.5311 (95.9817)
constant	408.5194 (495.6430)	379.9509 (500.2964)	393.0891 (468.9033)	361.4693 (472.7255)
Prob > χ^2	0.0289	0.0382	0.0514	0.0676
N	527	527	527	527
PARTICIPATION EQUATION: participation in continuing vocational training				
Influence on part. decision				
Strain	-0.4459*** (0.1276)	-0.4376*** (0.1279)	-0.4759*** (0.1296)	-0.4664*** (0.1301)
Prob > χ^2	0.0208	0.0249	0.0268	0.0272
ρ	-.1219	-.1148	-.1164	-.1102

Robust std. errors in parentheses; *** (0.01), ** (0.05), * (0.10).

Table A3.3: Increase in pay

	Basic equation			… & time preference			… & interaction terms			… & time preference, interaction terms		
	MLE	Probit model 2		MLE	Probit model 4		MLE	Probit model 6		MLE	Probit model 8	
	model 1	Coef.	ME	model 3	Coef.	ME	model 5	Coef.	ME	model 7	Coef.	ME
OUTCOME EQUATION: increase in pay												
Vocational training												
Apprenticeship	-0.0052	0.0366	0.0086	-0.0134	0.0300	0.0071	0.0091	0.0367	0.0087	-0.0005	0.0304	0.0072
	(0.2504)	(0.2559)	(0.0601)	(0.2474)	(0.2560)	(0.0602)	(0.2698)	(0.2518)	(0.0590)	(0.2642)	(0.2519)	(0.0591)
Full-time vocational school	0.0649	0.0241	0.0058	0.0620	0.0152	0.0036	0.0550	0.0335	0.0081	0.0521	0.0248	0.0060
	(0.3387)	(0.3242)	(0.0788)	(0.3368)	(0.3244)	(0.0782)	(0.3462)	(0.3239)	(0.0790)	(0.3479)	(0.3240)	(0.0784)
Master craftsman	-0.5705	-0.4757	-0.0907*	-0.5788	-0.4879	-0.0923*	-0.5378	-0.4852	-0.0917*	-0.5522	-0.4965	-0.0932**
	(0.3763)	(0.3301)	(0.0482)	(0.3565)	(0.3296)	(0.0474)	(0.4102)	(0.3303)	(0.0475)	(0.3881)	(0.3297)	(0.0467)
University of applied sciences	0.0351	0.1530	0.0391	0.0150	0.1501	0.0382	0.0543	0.1250	0.0315	0.0354	0.1230	0.0309
	(0.4285)	(0.3812)	(0.1040)	(0.4224)	(0.3815)	(0.1037)	(0.4915)	(0.3856)	(0.1025)	(0.4896)	(0.3866)	(0.1025)
University	-0.2816	-0.2176	-0.0469	-0.2962	-0.2355	-0.0502	-0.2694	-0.2258	-0.0483	-0.2894	-0.2430	-0.0515
	(0.3816)	(0.3767)	(0.0723)	(0.3765)	(0.3813)	(0.0717)	(0.4133)	(0.3747)	(0.0711)	(0.4034)	(0.3793)	(0.0705)
Professional status												
White-collar worker	0.3694	0.3951*	0.0906*	0.3631	0.3953*	0.0905*	0.3917*	0.3948*	0.0902*	0.3889*	0.3951*	0.0902*
	(0.2347)	(0.2132)	(0.0472)	(0.2369)	(0.2130)	(0.0471)	(0.2239)	(0.2183)	(0.0480)	(0.2275)	(0.2181)	(0.0479)
Self-employed person	-0.0216	-0.1150	-0.0261	-0.0340	-0.1443	-0.0322	-0.0533	-0.1040	-0.0236	-0.0681	-0.1333	-0.0298
	(0.4756)	(0.4377)	(0.0938)	(0.4752)	(0.4400)	(0.0915)	(0.5077)	(0.4456)	(0.0962)	(0.5146)	(0.4481)	(0.0939)
Employment characteristics												
Full-time employee	0.3105	0.2791	0.0625	0.3036	0.2681	0.0601	0.3590	0.3324	0.0732	0.3529	0.3209	0.0708
	(0.2374)	(0.2493)	(0.0518)	(0.2341)	(0.2473)	(0.0516)	(0.2771)	(0.2676)	(0.0539)	(0.2717)	(0.2654)	(0.0536)
Change	0.4587	0.5490***	0.1278***	0.4552	0.5614***	0.1305***	0.4998*	0.5418***	0.1258***	0.4999	0.5541***	0.1284***
	(0.3124)	(0.1736)	(0.0388)	(0.3141)	(0.1732)	(0.0386)	(0.2899)	(0.1757)	(0.0393)	(0.3051)	(0.1755)	(0.0392)
Meeting the needs	0.0344	0.0021	0.0005	0.0311	-0.0021	-0.0005	0.0066	-0.0066	-0.0016	0.0037	-0.0110	-0.0026
	(0.2499)	(0.2502)	(0.0596)	(0.2469)	(0.2492)	(0.0595)	(0.2561)	(0.2527)	(0.0604)	(0.2545)	(0.2515)	(0.0603)
Computer private	0.0229	0.1802	0.0407	0.0166	0.1887	0.0425	0.0894	0.1677	0.0379	0.0821	0.1757	0.0396
	(0.3882)	(0.2098)	(0.0448)	(0.3665)	(0.2100)	(0.0446)	(0.4103)	(0.2121)	(0.0455)	(0.4005)	(0.2123)	(0.0452)
Computer at work	-0.0013	0.1839	0.0419	-0.0115	0.1839	0.0419	0.0953	0.1853	0.0421	0.0826	0.1859	0.0422
	(0.4743)	(0.2176)	(0.0469)	(0.4350)	(0.2175)	(0.0468)	(0.4832)	(0.2177)	(0.0467)	(0.4582)	(0.2176)	(0.0466)
Number of employees	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Individual characteristics												
Age	-0.0027	0.0032	0.0008	-0.0010	0.0058	0.0014	0.0098	0.0102	0.0024	0.0125	0.0131	0.0031
	(0.0616)	(0.0635)	(0.0152)	(0.0615)	(0.0640)	(0.0153)	(0.0626)	(0.0631)	(0.0150)	(0.0627)	(0.0635)	(0.0151)
Age squared	-0.0002	-0.0002	0.0000	-0.0002	-0.0002	-0.0001	-0.0003	-0.0003	-0.0001	-0.0003	-0.0003	-0.0001
	(0.0007)	(0.0008)	(0.0002)	(0.0007)	(0.0008)	(0.0002)	(0.0008)	(0.0008)	(0.0002)	(0.0008)	(0.0008)	(0.0002)
Sex	0.0502	0.1183	0.0282	0.0538	0.1320	0.0314	0.1178	0.1416	0.0336	0.1252	0.1551	0.0367
	(0.2733)	(0.2304)	(0.0547)	(0.2708)	(0.2291)	(0.0543)	(0.2811)	(0.2611)	(0.0616)	(0.2845)	(0.2612)	(0.0615)
Kids	-0.3286	-0.3534*	-0.0847*	-0.3340	-0.3634*	-0.0870*	-0.4364	-0.4599	-0.1101	-0.4390	-0.4751	-0.1136
	(0.2069)	(0.1898)	(0.0459)	(0.2042)	(0.1881)	(0.0456)	(0.5959)	(0.5973)	(0.1438)	(0.5991)	(0.5945)	(0.1431)
Net income	0.0000	0.0001	0.0000	0.0000	0.0001	0.0000	0.0001	0.0001	0.0000	0.0001	0.0001	0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Married							-0.1688	-0.1019	-0.0252	-0.1884	-0.1083	-0.0268
							(0.4694)	(0.3679)	(0.0942)	(0.4682)	(0.3722)	(0.0956)
Single mother/father							-0.2362	-0.1445	-0.0323	-0.2575	-0.1456	-0.0325
							(0.6698)	(0.5408)	(0.1135)	(0.6737)	(0.5438)	(0.1138)
Male & kids							-0.1911	-0.1638	-0.0375	-0.1976	-0.1642	-0.0375
							(0.3803)	(0.3561)	(0.0781)	(0.3752)	(0.3565)	(0.0780)
Married & kids							0.2503	0.2399	0.0578	0.2519	0.2463	0.0593
							(0.5862)	(0.5948)	(0.1451)	(0.5787)	(0.5941)	(0.1448)
Time preference												
Present-oriented				-0.0394	-0.1006	-0.0236				-0.0684	-0.1021	-0.0238
				(0.2026)	(0.1696)	(0.0390)				(0.2138)	(0.1698)	(0.0389)
constant	-0.7730	-1.5787		-0.7070	-1.5615		-1.3224	-1.7008		-1.2493	-1.6844	
	(2.1637)	(1.3215)		(2.0278)	(1.3248)		(2.2655)	(1.3358)		(2.1782)	(1.3384)	
Prob > χ^2	0.1412	0.0203		0.1829	0.0210		0.1767	0.0524		0.2257	0.0519	
N	527	363		527	363		527	363		527	363	
PARTICIPATION EQUATION: participation in continuing vocational training												
Influence on part. decision												
Strain	-0.4109***			-0.4004**			-0.4539***			-0.4425***		
	(0.1563)			(0.1553)			(0.1473)			(0.1505)		
Prob > χ^2	0.6476			0.5945			0.8241			0.7850		
ρ	-.4713			-.5073			-.2566			-.3016		

Robust std. errors in parentheses; *** (0.01), ** (0.05), * (0.10); ME = marginal effect.

Table A3.4: Job security

	Basic equation MLE model 1		**… & time preference** MLE model 2		**… & interaction terms** MLE model 3		**… & time preference, interaction terms** MLE model 4	
	Coef.	ME	Coef.	ME	Coef.	ME	Coef.	ME
OUTCOME EQUATION: job security								
Vocational training								
Apprenticeship	0.0353	0.0101	0.0330	0.0095	0.0211	0.0060	0.0218	0.0063
	(0.1984)	(0.0561)	(0.1946)	(0.0555)	(0.2056)	(0.0586)	(0.2054)	(0.0592)
Full-time vocational school	0.1083	0.0321	0.1223	0.0366	0.0931	0.0275	0.1176	0.0354
	(0.2349)	(0.0715)	(0.2323)	(0.0717)	(0.2451)	(0.0741)	(0.2443)	(0.0756)
Master craftsman	0.2881	0.0909	0.3071	0.0980	0.1518	0.0460	0.1672	0.0515
	(0.2571)	(0.0875)	(0.2575)	(0.0887)	(0.2673)	(0.0846)	(0.2672)	(0.0858)
University of applied sciences	0.2548	0.0799	0.2619	0.0828	0.0777	0.0230	0.0750	0.0224
	(0.3601)	(0.1217)	(0.3554)	(0.1210)	(0.3823)	(0.1162)	(0.3761)	(0.1152)
University	0.0129	0.0037	0.0389	0.0114	-0.0355	-0.0101	-0.0030	-0.0009
	(0.3612)	(0.1047)	(0.3635)	(0.1081)	(0.3597)	(0.1009)	(0.3675)	(0.1068)
Professional status								
White-collar worker	-0.1842	-0.0533	-0.1922	-0.0561	-0.2119	-0.0616	-0.2201	-0.0647
	(0.1875)	(0.0550)	(0.1884)	(0.0556)	(0.1940)	(0.0574)	(0.1958)	(0.0587)
Self-employed person	0.0335	0.0097	0.0669	0.0198	-0.0095	-0.0027	0.0419	0.0124
	(0.3035)	(0.0892)	(0.3151)	(0.0955)	(0.3213)	(0.0918)	(0.3376)	(0.1013)
Employment characteristics								
Full-time employee	-0.1796	-0.0533	-0.1568	-0.0466	-0.1366	-0.0403	-0.1032	-0.0306
	(0.2115)	(0.0644)	(0.2129)	(0.0648)	(0.2270)	(0.0684)	(0.2301)	(0.0693)
Change	0.0511	0.0147	0.0327	0.0095	0.1051	0.0302	0.0849	0.0247
	(0.1394)	(0.0400)	(0.1419)	(0.0410)	(0.1457)	(0.0416)	(0.1491)	(0.0432)
Meeting the needs	-0.0547	-0.0160	-0.0567	-0.0167	-0.0645	-0.0189	-0.0638	-0.0189
	(0.2063)	(0.0613)	(0.2070)	(0.0619)	(0.2137)	(0.0639)	(0.2153)	(0.0650)
Computer private	0.1816	0.0504	0.1508	0.0424	0.2087	0.0578	0.1727	0.0488
	(0.1638)	(0.0438)	(0.1664)	(0.0454)	(0.1788)	(0.0471)	(0.1835)	(0.0495)
Computer at work	0.5136***	0.1382***	0.5174***	0.1403***	0.4949***	0.1338***	0.4931**	0.1350***
	(0.1712)	(0.0422)	(0.1763)	(0.0434)	(0.1854)	(0.0445)	(0.1920)	(0.0460)
Number of employees	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**	0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Individual characteristics								
Age	-0.0730	-0.0210	-0.0788	-0.0228	-0.1187*	-0.0342*	-0.1298**	-0.0378*
	(0.0573)	(0.0166)	(0.0594)	(0.0175)	(0.0646)	(0.0190)	(0.0659)	(0.0198)
Age squared	0.0009	0.0003	0.0010	0.0003	0.0014*	0.0004*	0.0015*	0.0004*
	(0.0007)	(0.0002)	(0.0007)	(0.0002)	(0.0008)	(0.0002)	(0.0008)	(0.0002)
Sex	0.4055**	0.1160**	0.3773*	0.1088*	0.6712***	0.1914***	0.6456***	0.1863**
	(0.1907)	(0.0543)	(0.1950)	(0.0563)	(0.2403)	(0.0690)	(0.2461)	(0.0727)
Kids	0.0640	0.0184	0.0824	0.0238	1.3130***	0.3646***	1.4028***	0.3918***
	(0.1574)	(0.0452)	(0.1592)	(0.0460)	(0.4860)	(0.1308)	(0.4769)	(0.1304)
Net income	-0.0001	0.0000	-0.0001	0.0000	-0.0001	0.0000	-0.0001	0.0000
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Married					1.0865***	0.2178***	1.1331***	0.2270***
					(0.3898)	(0.0514)	(0.4200)	(0.0532)
Single mother/father					0.1196	0.0358	0.1005	0.0302
					(0.4807)	(0.1487)	(0.4912)	(0.1516)
Male & kids					-0.4412	-0.1155*	-0.4596	-0.1214*
					(0.2912)	(0.0698)	(0.2979)	(0.0731)
Married & kids					-1.1481**	-0.3090**	-1.2057**	-0.3268***
					(0.4801)	(0.1221)	(0.4656)	(0.1202)
Time preference								
Present-oriented			0.1537	0.0453			0.2114	0.0630
			(0.1439)	(0.0435)			(0.1564)	(0.0489)
constant	0.0774		0.1218		0.1312		0.2083	
	(1.2193)		(1.2658)		(1.3269)		(1.3555)	
Prob > χ^2	0.0524		0.0799		0.0582		0.0724	
N	519		519		519		519	
PARTICIPATION EQUATION: participation in continuing vocational training								
Influence on participation decision								
Strain	-0.4521***		-0.4604***		-0.4774***		-0.4803***	
	(0.1214)		(0.1192)		(0.1230)		(0.1237)	
Prob > χ^2	0.0345		0.0589		0.0493		0.0923	
ρ	.8448		.8168		.7155		.6766	

Robust std. errors in parentheses; *** (0.01), ** (0.05), * (0.10); ME = marginal effect; none of the eight workers with a liberal profession could increase his/her job security considerably, which is why they are excluded.

Table A3.5: Prospects on the labor market

	Basic equation			… & time preference			… & interaction terms			… & time preference, interaction terms		
	MLE	Probit model 2		MLE	Probit model 4		MLE	Probit model 6		MLE	Probit model 8	
	model 1	Coef.	ME	model 3	Coef.	ME	model 5	Coef.	ME	model 7	Coef.	ME
OUTCOME EQUATION: prospects on the labor market												
Vocational training												
Apprenticeship	0.0351	-0.0491	-0.0196	0.0298	-0.0492	-0.0196	0.0244	-0.0495	-0.0197	0.0237	-0.0497	-0.0198
	(0.2067)	(0.2112)	(0.0842)	(0.2052)	(0.2110)	(0.0842)	(0.2341)	(0.2099)	(0.0837)	(0.2188)	(0.2097)	(0.0836)
Full-time vocational school	0.1715	0.1989	0.0792	0.1700	0.1983	0.0789	0.1596	0.1849	0.0737	0.1585	0.1845	0.0735
	(0.2396)	(0.2561)	(0.1014)	(0.2407)	(0.2558)	(0.1013)	(0.2491)	(0.2573)	(0.1020)	(0.2473)	(0.2570)	(0.1019)
Master craftsman	-0.1482	-0.3213	-0.1256	-0.1685	-0.3236	-0.1264	-0.2328	-0.3716	-0.1443	-0.2414	-0.3728	-0.1448
	(0.3064)	(0.2771)	(0.1047)	(0.2954)	(0.2774)	(0.1047)	(0.3844)	(0.2816)	(0.1046)	(0.3353)	(0.2822)	(0.1048)
University of applied sciences	0.7222**	0.6020	0.2306*	0.7311**	0.6028	0.2309*	0.7188*	0.5894	0.2264	0.7302*	0.5900	0.2266
	(0.3601)	(0.3784)	(0.1321)	(0.3624)	(0.3785)	(0.1321)	(0.4255)	(0.3950)	(0.1389)	(0.4110)	(0.3953)	(0.1390)
University	0.4527	0.4013	0.1576	0.4413	0.3988	0.1566	0.4818	0.4189	0.1643	0.4733	0.4174	0.1637
	(0.3225)	(0.3389)	(0.1282)	(0.3234)	(0.3388)	(0.1282)	(0.3335)	(0.3378)	(0.1273)	(0.3286)	(0.3375)	(0.1272)
Professional status												
White-collar worker	-0.2540	-0.2780	-0.1106	-0.2537	-0.2781	-0.1106	-0.2976	-0.3079	-0.1223	-0.2957	-0.3080	-0.1224
	(0.1839)	(0.1930)	(0.0763)	(0.1846)	(0.1930)	(0.0763)	(0.1914)	(0.1928)	(0.0760)	(0.1892)	(0.1928)	(0.0760)
Self-employed person	-0.3547	-0.2277	-0.0897	-0.3669	-0.2316	-0.0913	-0.4077	-0.3074	-0.1202	-0.4231	-0.3095	-0.1210
	(0.3692)	(0.3655)	(0.1414)	(0.3666)	(0.3674)	(0.1420)	(0.3997)	(0.3757)	(0.1422)	(0.3894)	(0.3770)	(0.1426)
Employment characteristics												
Full-time employee	0.3413	0.4630**	0.1811**	0.3424	0.4607**	0.1803**	0.3240	0.4315*	0.1691**	0.3192	0.4302*	0.1686**
	(0.2415)	(0.2147)	(0.0812)	(0.2347)	(0.2149)	(0.0814)	(0.3134)	(0.2211)	(0.0841)	(0.2782)	(0.2217)	(0.0844)
Change	0.1449	0.0842	0.0335	0.1504	0.0858	0.0342	0.1842	0.1322	0.0526	0.1898	0.1331	0.0530
	(0.1385)	(0.1418)	(0.0565)	(0.1404)	(0.1427)	(0.0568)	(0.1576)	(0.1450)	(0.0576)	(0.1529)	(0.1457)	(0.0579)
Meeting the needs	-0.3295	-0.3256	-0.1289	-0.3297	-0.3262	-0.1291	-0.3145	-0.3090	-0.1225	-0.3141	-0.3092	-0.1225
	(0.2159)	(0.2271)	(0.0882)	(0.2158)	(0.2271)	(0.0882)	(0.2237)	(0.2295)	(0.0895)	(0.2220)	(0.2295)	(0.0895)
Computer private	0.0080	-0.2038	-0.0811	0.0015	-0.2020	-0.0804	0.0168	-0.1411	-0.0562	0.0194	-0.1401	-0.0558
	(0.2495)	(0.1811)	(0.0718)	(0.2366)	(0.1819)	(0.0721)	(0.3315)	(0.1830)	(0.0728)	(0.2769)	(0.1839)	(0.0732)
Computer at work	0.4603**	0.2733	0.1081	0.4463**	0.2729	0.1079	0.4306	0.2793	0.1104	0.4243*	0.2791	0.1103
	(0.2008)	(0.1750)	(0.0683)	(0.1933)	(0.1748)	(0.0682)	(0.2787)	(0.1740)	(0.0678)	(0.2314)	(0.1739)	(0.0678)
Number of employees	0.0000**	0.0000*	0.0000*	0.0000*	0.0000*	0.0000*	0.0000**	0.0000*	0.0000*	0.0000**	0.0000*	0.0000*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Individual characteristics												
Age	0.0274	0.0163	0.0065	0.0273	0.0167	0.0066	-0.0130	-0.0178	-0.0071	-0.0132	-0.0176	-0.0070
	(0.0542)	(0.0564)	(0.0225)	(0.0544)	(0.0565)	(0.0225)	(0.0577)	(0.0585)	(0.0233)	(0.0574)	(0.0585)	(0.0233)
Age squared	-0.0004	-0.0003	-0.0001	-0.0004	-0.0003	-0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0007)	(0.0007)	(0.0003)	(0.0007)	(0.0007)	(0.0003)	(0.0007)	(0.0007)	(0.0003)	(0.0007)	(0.0007)	(0.0003)
Sex	-0.0639	-0.1471	-0.0586	-0.0618	-0.1449	-0.0577	-0.0999	-0.1441	-0.0574	-0.0980	-0.1433	-0.0571
	(0.2064)	(0.1994)	(0.0793)	(0.2064)	(0.1999)	(0.0795)	(0.2458)	(0.2351)	(0.0935)	(0.2399)	(0.2359)	(0.0938)
Kids	-0.1064	-0.1025	-0.0408	-0.1104	-0.1041	-0.0415	0.5841	0.6447	0.2525	0.5681	0.6424	0.2516
	(0.1568)	(0.1659)	(0.0660)	(0.1577)	(0.1665)	(0.0663)	(0.4935)	(0.4798)	(0.1814)	(0.4850)	(0.4812)	(0.1820)
Net income	-0.0001	-0.0001	0.0000	-0.0001	-0.0001	0.0000	-0.0001	-0.0001	0.0000	-0.0001	-0.0001	0.0000
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Married							0.9240***	0.8517**	0.3108***	0.9274***	0.8513**	0.3107***
							(0.3341)	(0.3567)	(0.1104)	(0.3346)	(0.3568)	(0.1104)
Single mother/father							0.4310	0.2760	0.1095	0.4396	0.2765	0.1097
							(0.5027)	(0.4860)	(0.1902)	(0.4892)	(0.4862)	(0.1902)
Male & kids							0.2168	0.1500	0.0598	0.2207	0.1508	0.0601
							(0.3057)	(0.2911)	(0.1159)	(0.2963)	(0.2908)	(0.1157)
Married & kids							-0.9948**	-0.9992**	-0.3809**	-0.9819**	-0.9981**	-0.3805**
							(0.4770)	(0.4844)	(0.1691)	(0.4732)	(0.4850)	(0.1693)
Time preference												
Present-oriented				-0.0890	-0.0181	-0.0072			0.0000	-0.0684	-0.0100	-0.0040
				(0.1496)	(0.1517)	(0.0604)			(0.0000)	(0.1628)	(0.1536)	(0.0612)
constant	-1.2189	-0.1794		-1.1379	-0.1761		-0.8605	-0.1098		-0.8231	-0.1073	
	(1.3568)	(1.1884)		(1.3160)	(1.1878)		(1.6400)	(1.1974)		(1.4291)	(1.1977)	
Prob > χ^2	0.0713	0.1515		0.1085	0.1884		0.0202	0.0746		0.0278	0.0945	
N	527	363		527	363		527	363		527	363	
PARTICIPATION EQUATION: participation in continuing vocational training												
Influence on part. decision												
Strain	-0.4044***			-0.4025***			-0.4351**			-0.4288***		
	(0.1402)			(0.1325)			(0.1692)			(0.1497)		
Prob > χ^2	0.3654			0.3096			0.6316			0.5241		
ρ	.6754			.6450			.5427			.5426		

Robust std. errors in parentheses; *** (0.01), ** (0.05), * (0.10); ME = marginal effect.

Table A3.6: Participation decision

	Basic equation		**… & time preference**		**… & interaction terms**		**… & time preference, interaction terms**	
	Probit model 1		Probit model 2		Probit model 3		Probit model 4	
	Coef.	ME	Coef.	ME	Coef.	ME	Coef.	ME
Vocational training								
Apprenticeship	0.3430*	0.1188*	0.3463*	0.1198*	0.3723**	0.1290*	0.3779**	0.1308*
	(0.1880)	(0.0671)	(0.1888)	(0.0674)	(0.1889)	(0.0678)	(0.1899)	(0.0681)
Full-time vocational school	0.0164	0.0054	0.0089	0.0030	-0.0170	-0.0056	-0.0228	-0.0076
	(0.2271)	(0.0748)	(0.2269)	(0.0749)	(0.2325)	(0.0775)	(0.2330)	(0.0778)
Master craftsman	0.7034**	0.1829***	0.6530*	0.1730**	0.6721*	0.1763**	0.6261*	0.1670**
	(0.3509)	(0.0646)	(0.3510)	(0.0681)	(0.3660)	(0.0691)	(0.3665)	(0.0725)
University of applied sciences	0.7351*	0.1866**	0.8126*	0.1991***	0.8566**	0.2054***	0.9437**	0.2172***
	(0.4238)	(0.0736)	(0.4194)	(0.0663)	(0.4199)	(0.0628)	(0.4149)	(0.0556)
University	0.4547	0.1299	0.4302	0.1238	0.5547	0.1519*	0.5315	0.1466*
	(0.3801)	(0.0897)	(0.3783)	(0.0912)	(0.3835)	(0.0818)	(0.3838)	(0.0836)
Professional status								
White-collar worker	0.0219	0.0073	0.0298	0.0099	-0.0127	-0.0042	-0.0051	-0.0017
	(0.1720)	(0.0572)	(0.1739)	(0.0578)	(0.1758)	(0.0581)	(0.1773)	(0.0586)
Self-employed person	-0.3484	-0.1248	-0.4091	-0.1479	-0.4324	-0.1566	-0.4925	-0.1798
	(0.3103)	(0.1179)	(0.3138)	(0.1208)	(0.3006)	(0.1160)	(0.3057)	(0.1191)
Employment characteristics								
Full-time employee	-0.2581	-0.0823	-0.2879	-0.0913	-0.3317*	-0.1042*	-0.3658*	-0.1140**
	(0.1892)	(0.0577)	(0.1894)	(0.0571)	(0.1939)	(0.0574)	(0.1949)	(0.0568)
Change	0.2387*	0.0791*	0.2650**	0.0877**	0.2687**	0.0888**	0.2960**	0.0976**
	(0.1271)	(0.0420)	(0.1285)	(0.0423)	(0.1290)	(0.0425)	(0.1302)	(0.0427)
Meeting the needs	-0.2111	-0.0665	-0.2021	-0.0637	-0.1975	-0.0622	-0.1917	-0.0604
	(0.1815)	(0.0541)	(0.1823)	(0.0545)	(0.1834)	(0.0549)	(0.1841)	(0.0552)
Computer private	0.5091***	0.1783***	0.5226***	0.1830***	0.5274***	0.1845***	0.5409***	0.1892***
	(0.1464)	(0.0534)	(0.1473)	(0.0537)	(0.1461)	(0.0532)	(0.1472)	(0.0536)
Computer at work	0.6318***	0.2180***	0.6146***	0.2118***	0.6399***	0.2204***	0.6214***	0.2136***
	(0.1460)	(0.0516)	(0.1469)	(0.0519)	(0.1464)	(0.0516)	(0.1475)	(0.0520)
Number of employees	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Individual characteristics								
Age	0.0274	0.0091	0.0257	0.0085	0.0018	0.0006	-0.0010	-0.0003
	(0.0506)	(0.0168)	(0.0508)	(0.0168)	(0.0527)	(0.0174)	(0.0527)	(0.0174)
Age squared	-0.0001	0.0000	-0.0001	0.0000	0.0001	0.0000	0.0001	0.0000
	(0.0006)	(0.0002)	(0.0006)	(0.0002)	(0.0006)	(0.0002)	(0.0006)	(0.0002)
Sex	0.1720	0.0571	0.1964	0.0651	0.1634	0.0541	0.1797	0.0594
	(0.1772)	(0.0588)	(0.1775)	(0.0588)	(0.2074)	(0.0685)	(0.2083)	(0.0687)
Kids	-0.0763	-0.0253	-0.0886	-0.0293	0.0748	0.0247	-0.0177	-0.0059
	(0.1500)	(0.0497)	(0.1510)	(0.0500)	(0.4211)	(0.1394)	(0.4260)	(0.1407)
Net income	0.0002*	0.0001*	0.0002*	0.0001**	0.0002*	0.0001*	0.0002*	0.0001*
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Married					0.6351**	0.2315**	0.6438**	0.2347**
					(0.2821)	(0.1086)	(0.2826)	(0.1088)
Single mother/father					0.7233*	0.1892***	0.7856**	0.2003***
					(0.3800)	(0.0728)	(0.3858)	(0.0692)
Male & kids					0.2143	0.0685	0.2296	0.0731
					(0.2654)	(0.0817)	(0.2660)	(0.0814)
Married & kids					-0.4184	-0.1396	-0.3426	-0.1141
					(0.4211)	(0.1407)	(0.4262)	(0.1424)
Time preference								
Present-oriented			-0.2718**	-0.0920**			-0.2796**	-0.0945**
			(0.1283)	(0.0441)			(0.1293)	(0.0444)
Influence on part. decision								
Strain	-0.4329***	-0.1466***	-0.4254***	-0.1439***	-0.4630***	-0.1565***	-0.4542***	-0.1533***
	(0.1261)	(0.0434)	(0.1264)	(0.0434)	(0.1280)	(0.0440)	(0.1285)	(0.0440)
constant	-1.4183		-1.2642		-1.1700		-0.9853	
	(1.0396)		(1.0450)		(1.0461)		(1.0501)	
Prob > χ^2	0.0000		0.0000		0.0000		0.0000	
N	527		527		527		527	

Robust std. errors in parentheses; *** (0.01), ** (0.05), * (0.10); ME = marginal effect

CHAPTER 4

Time – Even More Costly Than Money: Training Costs of Workers and Firms

4.1. Introduction

Continuing vocational training is becoming increasingly important, largely because of technological change and demographic trends. Today, occupations involve greater complexity than they did some decades ago (Spitz-Oener 2006). These changing job requirements come along with a growing demand for (highly) skilled labor and, as a consequence, for further training. In addition to the skill-biased technological change, there is evidence of depreciation of knowledge and skills (Janssen/Backes-Gellner 2009), which particularly affects older workers, who, due to recent demographic trends, form a constantly rising proportion of the workforce. Hence, continuing vocational training seems indispensable to make up for such effects and ensure sustainable labor market success.

Considering these developments, it is little surprising that numerous empirical studies provide evidence for training to have positive impacts on individuals' labor market outcomes (for an international overview see Bassanini et al. 2005, for Germany see Büchel/Pannenberg 2003): training is found to be associated with significant wage increase, lower risk of unemployment or higher promotion probability. But all of these studies focus on returns.

However, a worker's decision to undertake training is not only determined by expected rewards, but also by expected costs. Therefore, analyses focusing on benefits might not be able to fully explain the observed (non-)participation training patterns. There are only a few studies that consider training costs in detail. This is mostly due to a lack of appropriate data. In this study, we are fortunate to be able to use a dataset that provides extensive cost information. Hence, we analyze training probabilities with a focus on the cost component in order to determine how different types of costs affect workers' participation.

There are two important points to be noted regarding workers' training costs. First, employers can be involved in training decisions by sharing training costs, which makes firms important players for the outcome of training decisions. Accordingly, to explain training patterns we have to distinguish between the case in which training costs are (partly) covered by the firm, referred to as *employer-supported training* and the case in which the worker bears training costs entirely on their own, referred to as *self-financed training*. Second, there are different types of costs (as there are various types of benefits), which can be categorized in two main components: aside from the most obvious *monetary costs* (i.e., training expenses), there are also *non-monetary costs* (i.e., time spent in training) attached to participation.

In this study, we analyze training participation patterns and aim to discover the extent to which these are due to the combined effect of workers and employers decisions and the role of different training costs therein. In a first step, we study workers' probabilities of self-financing training conditional on receiving no employer support. In a second step, we examine the relation between the firms' and workers' training decisions.

As monetary and non-monetary costs can be expected to play different roles, all analyses are performed separately for these two cost components. In small firms, for instance, in which the production process is dependent on every single worker, participation during working hours might be excessively costly (as this would result in production loss). Nevertheless, support for a worker's training participation during leisure time might be possible. As another example, one could think of a worker with a long journey to work. Such a person might rather be willing to pay for training than to participate after working hours in the evening. Thus, we expect the distinction between the two groups of costs to be instructive for the understanding of training participation patterns.

To date, evidence regarding the joint training decisions of workers and firms (and thus training costs) has generally been scarce and is predominantly focused on employer-supported training (cf. e.g., Oosterbeek 1998 or Groot 1999). One notable exception is Bassanini et al., (2005) who simultaneously analyze the probability of employer-sponsored and non-sponsored training. The authors focus on differences in the impact of employment and individual characteristics on the respective training probabilities. However, they do not examine to what extent non-participation can be attributed to lack of employers' or workers' willingness to bear training costs, nor do they distinguish between the various cost components. Hence, when looking at employer-supported and self-financed training, we contribute to the existing literature by considering both monetary and non-monetary costs separately and by studying

workers' willingness to completely bear training costs. This might help in understanding the issue of training (non-)participation.

The conceptual difficulty in analyzing these issues is that we observe whether a worker participates in training without knowing the reason why or why not. It is challenging to disentangle the effect of either side on the result, since we have no information on the individual decision of one of the parties if the other has decided differently – or even similarly. However, we are fortunate to be able to utilize a unique dataset of both participants and non-participants, which for the first time provides extensive cost information. It particularly provides separate and detailed information on monetary and non-monetary costs associated with training participation.

Based on this data, we are able to disentangle the firms' and the workers' impact on training decisions. Our findings show, first, that those workers who are considered for employer-supported training would also be more likely to have self-financed their training had they not received this support. Second, looking at the two cost components separately, we find that for workers the willingness to bear monetary costs is much higher than it is to bear non-monetary costs, which emphasizes the importance of distinguishing between various cost components.

The structure of the chapter is as follows: in the next section we present some theoretical considerations concerning the training decisions of workers and firms. Subsequently, section 4.3 details the econometric model. In section 4.4 we describe the participants and non-participants survey and provide some descriptive statistics concerning the probability of employer-supported versus self-financed training participation. The results of the empirical investigation are presented in section 4.5, and conclusions are drawn in the final section.

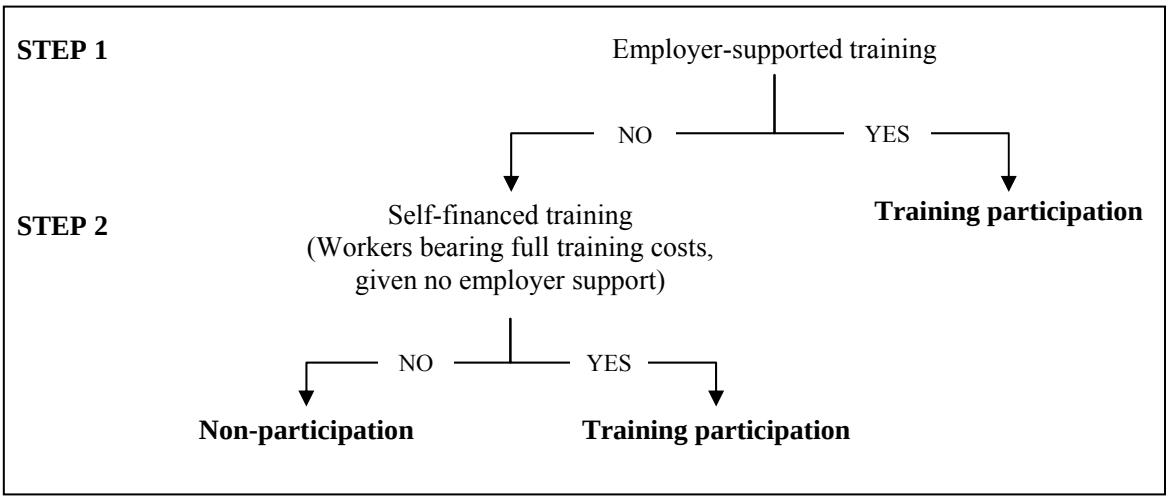
4.2. Theoretical framework of the training decisions of workers and firms

Following Bassanini et al. (2005: 71-72), we assume that training decisions are undertaken sequentially (cf. Figure 4.1): first, a firm decides whether to support a worker's training participation. We argue that employer-supported training is part of a worker's job and thus that there is no (subsequent) decision for the worker whether to accept training.[44] This is why employer-supported training directly results in a worker's training participation. If the employer does not provide training support, the worker chooses whether or not to bear the full training costs himself. Thus, we distinguish between two types of training: on the one hand,

[44] Of course, some workers might also refuse to participate, even though they would receive employer support. However, we assume that such cases constitute an exception. First, in our dataset, some training participants report being forced to undertake training. Second, most non-participants report a lack of employer support as (one) cause of their non-participation (indicating the importance of employer-support).

we consider workers whose training costs are (partly) covered by their firm. This case will be referred to as *employer-supported training*. On the other hand, we consider workers who lack employer support and must bear the entire training costs alone. This case will be referred to as *self-financed training*.

Figure 4.1: Sequence of training decisions



To analyze the two subsequent training decisions of firms and workers, we use standard human capital theory (Becker 1975) as a framework. Each party can be supposed to invest in training if their expected benefits exceed their expected costs. The cost-benefit ratio and thus the willingness to bear training costs vary between workers and firms according to personal attributes, employment characteristics, and training content.

As concerns the latter (i.e., training content), the most prevalent distinction is between general and (firm-) specific human capital. We will show in the following two paragraphs that firms basically pay for training that imparts either type of knowledge:

In the standard analysis of human capital, it is argued that costs and returns to investments in *specific human capital* are shared by firms and workers because of uncertainty about post-investment behavior (Becker 1962) or because of the existence of transaction costs in evaluating and agreeing on a worker's productivity (Hashimoto 1981). Sharing investments therefore reduces the risk of separation and of losing a portion of an investment. It should be noted that sharing of human capital investments is expected to be widely observed, independent of the exact concept of specific human capital. Becker (1962), on the one hand, argues that much of the training has general as well as specific components but increases the worker's productivity more for the firm providing the training and is therefore referred to as specific training. In contrast, Lazear (2003) considers all training as general, but he assumes that each firm requires only a specific combination of skills.

When training is perfectly general, workers can capture the entire return to training (because *general human capital* would be just as useful in other firms) and, consequently, they also have to bear the full costs associated with training participation. This supposition, however, only holds as long as the labor market is assumed to be perfectly competitive. As soon as this assumption is relaxed, employers can again be expected to share in training investments. If the worker's wage is below his productivity level, and the difference increases with skill level (due to a compressed wage structure), the employer has an incentive to invest in training because he can capture some of the return (see for example Acemoglu/Pischke 1999 or Booth/Zoega 2004). Thus, employers can generally be expected to pay for (firm-) specific as well as supposedly general human capital; therefore, we consider training of either content in our empirical analyses.

In the following paragraphs, we briefly specify which personal and employment attributes are expected to be associated with favorable cost-benefit ratios for firms, and we do the same for workers. Starting with individual characteristics, theoretical predictions concerning workers' and employers' training decisions are (mostly) identical. For instance, one usually assumes a complementarity between *education* and training, in which more educated workers are expected to have a greater willingness to undertake training, as well as a higher probability of being selected for employer-supported training.[45] The same applies to motivation and training because they are also assumed to exhibit a complementary relationship. As concerns *gender differences*, male workers can be expected to have a higher average training probability.[46] This again applies for employer-supported as well as for self-financed training. First, one would expect the probability of being selected for training by the employer to be higher for individuals who are regarded as being more committed to the firm. As Booth (1991: 285) points out, in preferring workers who seem more committed to the firm, employers discriminate against women. Secondly, the higher willingness of male workers to undertake training might arise from differences in preferences. These gender differences might even be more pronounced in the group of workers with *children* – i.e., having children might further reduce the average training probabilities of women.[47] Finally, following human capital theory,

[45] Mincer (1962: 59) might have been the first to suggest the notion of complementarities between education and training, stating that school education has to be seen as a prerequisite for further training. Rosen (1976) specifies that more education enables individuals to exhibit greater job learning efficiency.

[46] It should be noted that in looking at participation patterns for women, as compared to those for men, one has to distinguish two sources of variability (Arulampalam et al. 2004: 355): on the one hand, the two groups might differ in respect of personal attributes and employment characteristics, while on the other hand there might also exist differences in the returns to training in the context of similar exhibited characteristics. This is why we perform separate analyses for men and women.

[47] From an employer's perspective, women with young children are usually expected to have a weaker attachment to the labor market than are men with young children. From an individual's perspective, having

one would expect *younger* and *full-time workers* to have higher training probabilities than *older* and *part-time workers* because the expected pay-off period for the former two groups is longer. Generally, this effect operates through both channels (i.e., through both workers' and firms' decisions). However, for the employer it is not so much mere age as the expectation of how long the worker will stay in the firm which is important. As older employees might find it more difficult to secure better job matches, they have a lower probability of leaving. Thus, it may as well be less risky for the employer to invest in these workers, which in turn might counteract the effect of a longer expected pay-off period for younger workers. So the overall effect is not clear ex ante.

To summarize, almost all individual characteristics are expected to have no systematically different impacts on the training decisions of firms and workers. As employment characteristics are generally expected to predominantly operate through the employers' decision to support training (because they influence companies' training costs and benefits) they do not affect (or at least do not counteract) this positive correlation between the two training decisions. Thus, we expect the two training decisions to be related as follows:

> *Those workers who receive employer-supported training are also the ones more likely to have borne the full training costs themselves had they not received employer support.*

Of course, this hypothesis is difficult to test because we have no data regarding what would have occurred had the worker not received employer-supported training. Thus, we need an econometric method that will help us to disentangle the two effects and estimate the counterfactual (i.e., what would have happened if those workers who receive employer-supported training had not received such support).

Though a worker's true willingness to bear the full training costs might as well be hidden for the firm, the latter might have a guess about the worker's training decision in case of not being selected for employer-supported training. This question will be addressed in the empirical part. In the next section, we detail the exact estimation procedure applied to test the hypothesis.

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children might be associated with a substantial increase in the discount rate; on the other hand, and this might be especially true for male workers, having children might involve greater responsibilities and consequently a greater motivation to accumulate new human capital (Arulampalam/Booth 2001: 387), which could then counteract the aforementioned negative effect.

4.3. Modeling the worker's and firm's decision to bear training costs

In the first step of the analysis, the goal is to sort out which factors determine the probability of receiving employer-supported training and which factors impact individuals' willingness to self-finance training participation. As it is likely that there exists a link between the firm's and the worker's training decisions, we use an empirical framework that explicitly takes account of this potential dependence. In a second step, based on these estimations, we calculate predicted training probabilities and assess whether those workers whose firm covers (part of) the training costs would have borne the full costs themselves had they not received employer support. Finally, we examine the relation between the two training decisions.

4.3.1. Employer-supported training

The likelihood of a worker to take part in training primarily depends on the probability of receiving employer support. Firms are expected to select those workers who have the ability to benefit from training as well as those who are likely to remain with the firm after training. To estimate the impact of these characteristics on the probability of employer-supported training, we use the following probit model framework:

$$\begin{aligned} y_f^* &= \beta \cdot P_f + \gamma \cdot E_f + \varepsilon_f \\ y_f &= 1 \text{ if } y_f^* \geq 0 \\ y_f &= 0 \text{ if } y_f^* < 0 \end{aligned} \qquad (4.1)$$

The latent index y_f* models the underlying process of a firm's decision to support an employee's training participation by bearing (part of) the training costs. If a worker receives employer-supported training, y_f takes the value one, and zero otherwise. P_f and E_f represent vectors of personnel characteristics and employment characteristics, respectively; ε_f indicates the error term. Receiving employer support for training participation might be a strong predictor of actual participation. Nevertheless, we also observe workers who lack employer support and individually arrange and finance their participation (e.g., Greenhalgh/Malvrotas 1994). Hence, we additionally have to analyze the probability that a worker bears full training costs conditional on **no** employer support.

4.3.2. Workers bearing full training costs, given no employer support

Following Bassanini et al. (2005: 71-72), we assume that training decisions are undertaken sequentially (cf. section 4.2). The problems to be solved in the empirical analysis are, first, that the two decisions are expected to be related, and second, that all workers are obviously

only observed in one situation (i.e., we do not know what would have happened if those workers who receive employer-supported training had not received such support). Thus, we have a censored dependent variable and a potentially selected sample of workers in the second step of the analysis.

The model to be used for such a framework is the censored bivariate probit model (Van de Ven/Van Praag 1981): the probability of receiving employer-supported training is observed for the full sample of workers. But for the second step, the probability that a worker bears full training costs, there is a censored dependent variable and a potentially selected sample of workers. The model takes account of a potential correlation ρ of unobserved factors that have an impact on both equations, and we jointly estimate both equations with maximum likelihood. Although the bivariate probit with censoring does not require an exclusion restriction (i.e., a variable that has an impact on the selection equation but that does not affect the outcome equation), we include an additional variable that satisfies the exclusion restriction. Hence, the model structure can be written as follows:[48]

$$\begin{aligned} &y_f=1\text{: Prob } (y_f=1|x_w, x_f) \\ &y_w=0, y_f=0\text{: Prob } (y_w=0, y_f=0|x_w, x_f) \\ &y_w=1, y_f=0\text{: Prob } (y_w=1, y_f=0|x_w, x_f) \end{aligned} \qquad (4.2)$$

where y_w takes the value one if a worker self-finances his training participation and zero otherwise. This decision is expected to be determined by personal and employment characteristics reflected in x_w. Similarly, y_f indicates employer-supported training and, thus, x_f is a vector consisting of the aforementioned personnel (P_f) and employment (E_f) characteristics. According to this model, there are three observations to be distinguished and three probabilities to be estimated. Based on these estimations, we then calculate the predicted probability of self-financing participation for the full sample (cf. section 4.3.3).

We are not the first to use the bivariate probit model with censoring to analyze training decisions. Bassanini et al. (2005) also estimate a bivariate probit with censoring, in which employers decide on whether to pay for workers' training, and unsupported workers then choose whether or not to self-finance their training participation. Oosterbeek (1998) has also used this framework, but, instead of considering self-financed training, he focuses on employer-supported training and models the distinct decisions of firms and workers. Unlike in our framework, employer-supported training is conditional on a worker's willingness to participate. The fact that, in our dataset, some workers report being forced to participate in training, leads us to prefer the framework introduced by Bassanini et al. (2005).

[48] The notation is based on Greene (2003: 713-714).

A test of our hypothesis requires information about each workers' willingness to bear training costs (i.e., also for those who currently receive employer support). In the next section, we explain how these probabilities of workers to bear full training costs are estimated.

4.3.3. Predicted probabilities that workers would bear the full training costs

Before comparing the probabilities that workers will bear full training costs when not receiving employer-supported training, it is first necessary to address the problem that this probability can only be observed for those not currently receiving employer-supported training. Therefore, based on the estimation described above, we calculate a hypothetical conditional probability[49] for self-financing training. This can be accomplished for the full sample of workers and allows for testing the hypothesis that those workers who receive employer-supported training would also have been more likely to have borne the full training costs themselves had they not received employer support. Moreover, we are interested in learning whether the results depend on the cost measure, i.e., whether using monetary and non-monetary costs (in combination or separately) influences the estimation results. Thus, we first perform all analyses using one cost measure that includes both monetary and non-monetary costs, and then proceed to use two different cost measures, one for the monetary and one for the non-monetary cost component.

4.3.4. Relation of workers' and firms' training decisions

Finally, we are interested in finding out whether a worker's individual person-specific willingness to bear full training costs is incorporated in the firm's decision to support training. The reason is, that, as mentioned in the theoretical section, firms might have a guess about the worker's training decision in case of not being selected for employer-supported training. Therefore, we augment the probit model presented in section 4.3.1 (equation (4.1)) to incorporate the worker's willingness to bear the full training costs.

4.4. Data: survey of participants and non-participants

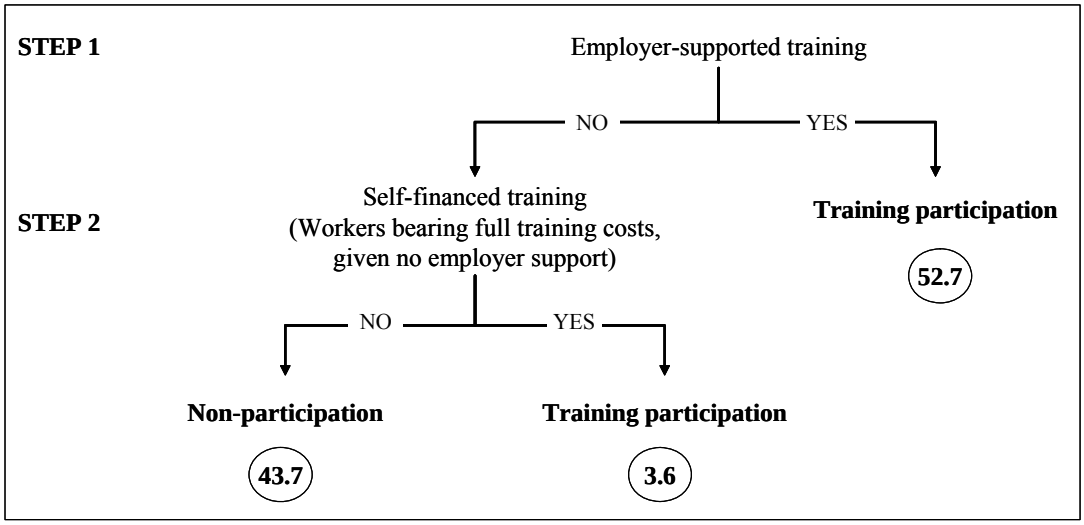
The availability of detailed cost information associated with workers' training participations is a necessary precondition for examining the questions raised in our study. We are fortunate in being able to use a dataset that provides such extensive cost information. Individuals from a

[49] Pr(self-financed training=1|employer-supported training=0). It should be kept in mind that this probability is different from the "actual" unconditional probability Pr(self-financed training=1, employer-supported training=0).

large representative sample (of Germany) were contacted by telephone and asked whether they had taken part in continuing training in a given period. According to their answer, they were either allocated to the participants' surveys (further analyzed by Beicht et al. 2006) or to the non-participants' surveys (further analyzed by Schröder et al. 2004).[50] For each sample, the telephone interviewers used a questionnaire specifically designed for the respective respondents. Moreover, there was a list of common questions that individuals in both groups were asked to answer, which allows the pulling together of the two datasets. In this chapter, we use data from both the participant and non-participant surveys.

Most importantly, this rich dataset allows for the categorization of training participants into those who receive employer-supported training and those who bear the full costs of training. The two variables representing the firms' and workers' training decisions are defined as follows: the variable *employer-supported training* takes the value one if the employer bears (part of) the training costs (i.e., covers monetary training costs and/or offers training participation during working hours) and zero otherwise.[51] The variable *self-financed training* takes the value one if the worker bears full training costs and zero otherwise. We note that the term self-financed training refers to both monetary and non-monetary costs. Descriptive statistics for the three outcomes of the sequence of training decisions are given in Figure 4.2:

Figure 4.2: Training participation patterns



Note: the numbers in circles indicate percentages.

Considering full costs, 52.7% of the workers in the sample participated in employer-supported training, i.e., their firm covered monetary training costs, provided training during working

[50] For information about the survey design, see Krekel/Walden (2007).

[51] There is a non-negligible proportion of workers reporting no costs. This seems unrealistic for job-related training and is therefore classified as employer-supported training (coincident with Booth/Bryan 2007).

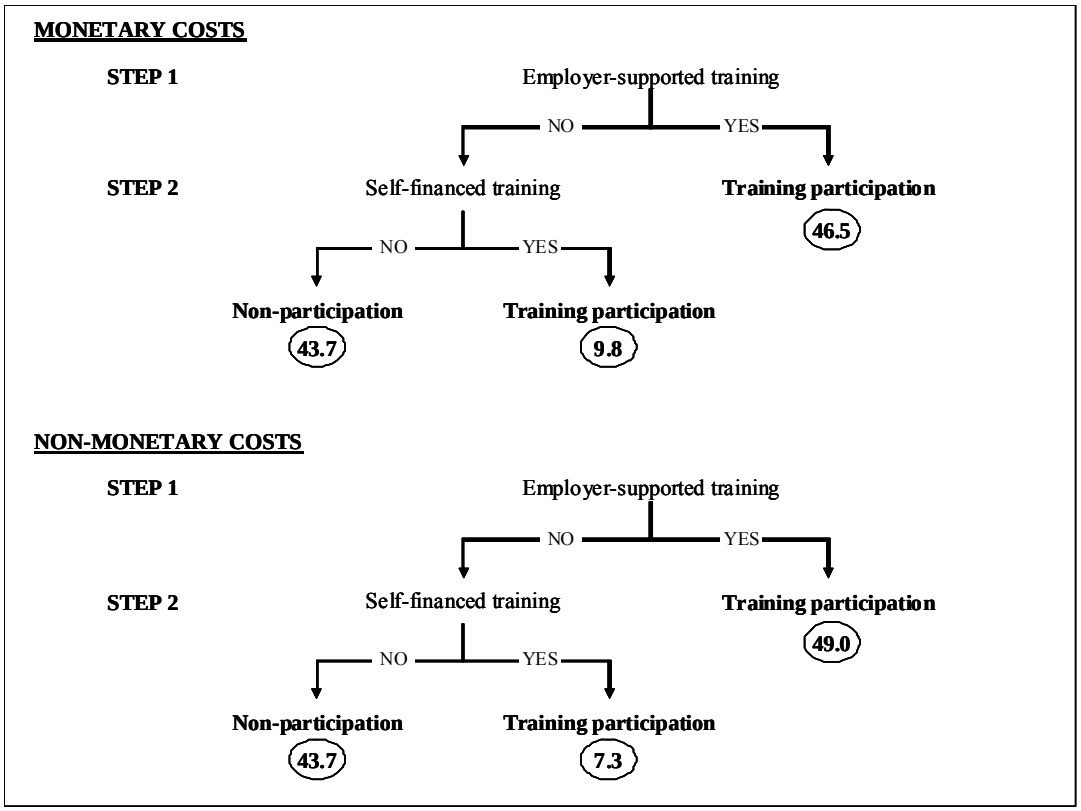
hours, or partially/fully covered both types of training costs.[52] In contrast, 3.6% of the employees bore full training costs, i.e., training participation occurred completely during leisure time and the workers bore all training expenses. The remaining workers (43.7%) are not participating in training.

As already mentioned, training investments involve both money (referred to as *monetary costs*) and time (referred to as *non-monetary costs*). This distinction is rarely – if at all – found in the training literature. For future research, however, it is important to know whether using monetary and non-monetary costs matters, either separately or in combination. Looking at monetary and non-monetary costs separately, the dependent variables are defined as follows: in relation to *monetary costs*, *employer-supported training* is defined as firms covering (part of) the pecuniary training costs and *self-financed training* participation involves workers bearing full training expenses; with regard to *non-monetary costs*, a worker receives *employer-supported training* if training participation occurs (at least partly) during working hours, and undertakes *self-financed training* if participation occurs exclusively during leisure time.

The distribution of participants in employer-supported and self-financed training, categorized in terms of monetary and non-monetary costs, is shown in Figure 4.3. It should be noted that, in looking at monetary costs separately, we do not consider how much employer support workers receive in terms of non-monetary costs (and vice-versa). In Figure 4.2, workers are categorized by whether they received employer-supported training independent of whether they obtained support in terms of both cost components. Figure 4.3 categorizes workers by the support they received in terms of particular cost components. Thus, if not all workers received employer support for both cost components, the numbers in employer-supported training should be lower and the numbers in self-financed training higher.

[52] Although individuals are not asked to report which part of the financial assistance is provided by the firm, the government, or the unemployment insurance system, the assumption of the firm being the main funding source should not be very strong because the sample analyzed conditions on employment.

Figure 4.3: Training participation patterns for monetary/non-monetary costs



Note: the numbers in circles indicate percentages.

Considering the firms' decisions, there appears to be no significant difference between the two cost components; the probability that training occurs during working hours is slightly higher than the probability of receiving financial assistance, though both approach 50 percent. In contrast, the workers' average willingness to bear training costs varies by the type of cost: workers whose firms do not cover monetary costs are more likely to participate regardless and therefore to bear full training expenses than are those who lack employer support in terms of non-monetary costs. This confirms the assumption that time must be seen as a critical factor in workers' training decisions.

Comparing these numbers with the distribution obtained when using only one cost measure, this indicates that most training participants are supported in terms of both cost components. Figure 4.4 shows how monetary and non-monetary support are related. Not surprisingly, the vast majority of workers receive employer support in terms of either both cost components or neither. With regard to employees whose firm covers either exclusively monetary or exclusively non-monetary costs, the latter is much more frequent (6.2% versus 3.8%), but both situations are quite rare.

Figure 4.4: Percentage of workers receiving monetary and/or non-monetary employer support

Workers receiving….		Non-monetary support		Total
		YES	NO	
Monetary support	YES	**42.7 %**	**6.2 %**	48.9 %
	NO	**3.8 %**	**47.3 %**	51.1 %
Total		46.5 %	53.5 %	100 %

In summary, employer-supported training seems far more widespread than wholly self-financed training, and this conclusion is in line with existing evidence.[53]

As has been shown in section 4.2, the cost-benefit ratio and thus the willingness to bear training costs are determined by individual and employment characteristics. Hence, the explanatory variables used in our empirical analyses are those characteristics presented in the theoretical section. They correspond to the variables typically used in studies that deal with the determinants of training participation.[54] The choice of independent variables is especially comparable to Bassanini et al. (2005), which is the study most similar to our empirical analyses.

In those specifications which are used to test hypothesis two (which focuses on the relation between the firms' and workers' training decisions), we additionally include a variable representing a worker's willingness to bear monetary costs as well as a proxy for a worker's willingness to sacrifice leisure time for training participation. The latter variable is a dummy variable taking the value one if the worker states that at present he is short of time for training participation.

Concerning training content, which can also be assumed to influence cost-benefit ratios of training, we have shown that employer support is theoretically expected for general as well as specific human capital. Therefore, we do not restrict our analyses to one type of training content. Quite the contrary, the training definition which underlies our analyses includes an extensive range of training types[55], namely self-organized learning, training programs that take place at continuing vocational training institutes, schools or the companies themselves,

[53] According to Bassanini et al. (2005: 56-60), cross-country variation in employer-sponsored training courses is large. But even in countries with a relatively high share of non-sponsored training, such as in Switzerland, Ireland or Italy, the share of employer-sponsored training is at least 50%.

[54] There is no information about union membership in the dataset, so such a variable cannot be included. However Pischke (2001) argues that union coverage would be the relevant concept, which is almost universal in Germany anyway.

[55] See Table A4.1 in the Appendix.

participation at a congress or conference, and job-related types of training.[56] Thus, using such a broad training definition, we also identify participants in less formal and, in previous studies, less commonly included types of training.

For our empirical analyses, the sample is restricted to employed workers in the private sector. The reason for this focus is that our study analyzes the role that employers play in workers' training decisions. In the case of unemployed or non-employed persons, there is no employer at all. Self-employed persons are their own employer and civil servants are supposed to be in a different situation with regards to funding training costs, as they are paid by public authorities. Moreover, we only include workers aged 25-64, and we exclude any employees from the agriculture and forestry sectors. After additionally deleting all respondents who have missing information in one of the above variables, 1,365 observations remain. Variable definitions and certain descriptive statistics are in Table A4.2 in the Appendix.

4.5. Estimation results for the training decisions of workers and firms

To analyze the two subsequent training decisions, we first estimate the probability of employer-supported training. Second, we estimate the probability of self-financed training conditional on receiving no employer support. Based on these estimations, we then predict the willingness to bear training costs for the full sample of workers in order to test our hypothesis. Finally, we examine whether the worker's willingness to bear training costs is incorporated in the firm's training decision. We perform all analyses using one cost measure that includes both monetary and non-monetary costs and then proceed to use two different cost measures, one for the monetary and one for the non-monetary cost component.[57]

4.5.1. Analysis of employer-supported training

We start by looking at the probability of employer-supported training. The estimation results of the probit model are presented in Table A4.3, column 1, in the Appendix.[58] The findings are broadly consistent with the theoretical considerations presented in section 4.2: workers with a secondary or tertiary educational degree, who are highly motivated for participation in

[56] Of course there might be differences in the intensity of the involvement of firms dependent on the training content. Unfortunately, however, for those individuals who have taken part in more than one training type it is not possible to assign employer support to the various training participations. Therefore, we cannot distinguish between the various training types in our empirical analyses.

[57] It should be noted that all our analyses focus on training costs and do not explicitly model the benefits resulting from participation. The underlying assumption is that workers and firms who decide to invest in training do so with the expectation of positive returns.

[58] The probit estimates, presented in Table A4.3, have been transformed to show the marginal effects at the mean using the estimation procedure explained in Bartus (2005). We proceed in this way throughout the section.

training, who are full-time employed, or who are below 35 years of age all have higher training probabilities. The former two findings confirm the assumption that there is a complementarity between further training and formal education[59] as well as motivation; the latter finding is in line with human capital theory, which predicts the incentive to invest in training to be higher the longer is the expected pay-off period. Interestingly, none of the variables that reflect gender or family caring responsibilities seem to determine the likelihood of training. Thus, there is no evidence either for discrimination or for employers selecting workers on the basis of their perceived commitment to the firm.

Regarding employment characteristics, being a white-collar worker, facing changing knowledge and skill requirements and being employed in a large enterprise are all associated with substantially higher probabilities of receiving employer-supported training. This is consistent with the assumption that the production process and resulting skill requirements considerably impact a firm's training decision. Lastly, larger firms have a higher training probability, which might be due to economies of scale (i.e., fixed costs can be divided between more workers), lower production losses from absent workers (who are away from their jobs during the training period), or reduced risk of poaching externalities because of, for example, the existence of internal labor markets, which provide career opportunities (Lynch/Black 1998: 65-66).

Besides the individual and employment characteristics we include an additional variable indicating the training fraction by industry. In a next step (cf. section 4.5.2), in which we analyze the probability of self-financing training conditional on receiving no employer support, this variable is used as an exclusion restriction. The variable satisfies the exclusion restrictions and therefore qualifies for an instrumental variable because it correlates with the probability of receiving employer-supported training. [60]

Looking at monetary and non-monetary costs separately, the main patterns found in the analyses which has been performed by using a cost measure that includes all types of training are confirmed. The estimation results are shown in Table A4.4 and A4.5, column 1, in the Appendix. The most striking difference concerns the gender effect. Male workers are significantly more likely to receive employer support in terms of non-monetary costs than are female workers. This finding might be due to gender differences in negotiations. There is, for instance, empirical evidence that women compared to men ask for less in pay negotiations

[59] Of course, we cannot rule out the possibility that estimates of the effects of education also pick up ability. However, for the purposes of this study, this is not crucial. Therefore, we do not present an elaborate discussion of the existence of a potential heterogeneity bias.

[60] Moreover, it seems plausible to assume that after controlling for industry sector, the training fraction by industry should not have an impact on the probability of self-financing training participation.

(see for example Säve-Sörderbergh 2007). In the case of training this gender-specific behavior might result in a lower probability of being released from work to participate in training. Interestingly, regarding monetary costs, we do not find a difference between the two genders. We interpret this difference in terms of the two cost components as an indication that firms are rather willing to cover monetary costs than to provide training participation during working hours. To receive the latter, considerable negotiation skills might be essential.

Of course, separate estimations for male and female workers might be more appropriate for the analysis of training participation patterns. Therefore, we additionally provide the results of separate estimations by gender (cf. Table A4.3, column 2 and 3, in the Appendix). The main differences between male and female employees can be summarized as follows: for female employees, being aged below 35, having children, and being employed part-time is associated with a significantly lower probability of receiving employer-supported training. Firms might associate all these characteristics with a lower attachment to the firm. For male workers, however, this does not apply: none of these characteristics turns out to be significant. With the exception of the child effect, these results also hold when looking at monetary and non-monetary costs separately (cf. Table A4.4 and A4.5, column 2 and 3, in the Appendix). Interestingly, for women, having children "solely" affects the probability of (not) being supported in terms of non-monetary costs. This supports our assumption that distinguishing between the two cost components is important for analyzing training decisions, as firms seem to provide differing support in terms of monetary and non-monetary costs.

4.5.2. Analysis of workers bearing full training costs given no employer support

Those workers who do not receive employer-supported training might consider bearing the full training costs themselves. To analyze the probability of self-financing training conditional on receiving no employer support, we estimate a bivariate model with censoring that takes into account unobserved factors influencing the firm's and worker's training decisions. The hypothesis that the correlation ρ between the selection equation and the outcome equation is zero cannot be rejected.[61] This implies that those factors that are not controlled in our estimations but that do affect training decisions are not the same (or at least are not correlated) across workers' and firms' decisions. This is not surprising, given that we suppose to have included most of the variables that can be assumed to exert influence on both decisions. Thus,

[61] Bassanini et al. (2005) do find a selection effect for sponsored and non-sponsored training. Their definition of training and of sponsored vs. non-sponsored training is very different, however, meaning that the results are not directly comparable.

we can use a simple probit model to estimate the outcome equation.[62] The results are shown in Table A4.3, column 4, in the Appendix.

Except from the finding that the education level does not (significantly) affect the probability of receiving employer-supported training, all variables show the expected influence: more motivated, childless and middle age workers are more likely to still participate in training even though they are not selected for employer-supported training.

As soon as we separately consider monetary and non-monetary costs, we find an education effect (cf. Table A4.4 and A4.5, column 4, in the Appendix). Better-educated workers have a higher willingness to pay for training as well as to sacrifice leisure time for training participation. This is in line with the theoretical predictions, which suppose a complementarity between education and training, resulting in a more favorable cost-benefit ratio for highly educated workers. The puzzle to be solved is why these workers, for whom training participation is individually beneficial, are not supported by their employer. One explanation is to be found in the differing expectations concerning the continuation of the work relation. For instance, firms might expect highly educated workers to have attractive outside options, for which reason the risk of losing an investment in training is high. This assumption is supported by the fact that workers with tertiary education are overrepresented in the group of employees who self-finance their training participation.

Although none of the estimations indicates a gender effect, we briefly sketch the most interesting result when performing separate estimations. In contrast to the estimations of employer-supported training, we find that for women having children reduces the willingness to pay for training but does not influence the willingness to bear non-monetary costs. For male workers, we again do not find a difference.

4.5.3. Analysis of predicted probabilities that workers would bear the full training costs

Given that the share of self-financed training is much smaller than that of employer-supported training, it is even more important to know who is able and willing to bear full training costs. Thus, as a next step, we predict the probability of self-financing training for the full sample of workers, conditional on receiving no employer-supported training (cf. Table 4.1).

[62] As the hypothesis that the correlation between the two equations is zero cannot be rejected for either estimation performed, we proceed in this way throughout the section.

Table 4.1: Predicted training probabilities conditional on receiving no employer support, including all types of costs

	Workers who currently receive employer-supported training			Workers who do **not** receive employer-supported training			Mean comparison test		
	Full Sample	Male Workers	Female Workers	Full Sample	Male Workers	Female Workers	Full Sample	Male Workers	Female Workers
Monetary and non-monetary costs	0.1516 (0.0058)	0.1715 (0.0084)	0.1197 (0.0094)	0.0759 (0.0043)	0.0911 (0.0070)	0.0355 (0.0042)	***	***	***

This predicted probability is, on average, 7.59% for those presently not receiving employer-supported training, and 15.16% for those whose training costs are currently shared or completely covered by the firm. A mean comparison test shows that the difference between these average predicted probabilities is highly significant. Thus, the results are consistent with our hypothesis: those who currently receive employer support would also have a higher probability of still participating in training had they not received this support. The fact that firms support some workers who would also be willing to bear the full training costs seems counterintuitive, at least at first sight, and should be investigated in more detail. One explanation could be that firms pursue various associated side benefits by providing training, such as increasing employees' commitment to the firm or signaling good career opportunities to outside workers. We will discuss various explanations in the next section.

Performing separate estimations by gender demonstrates that female workers are systematically less likely to bear the full training costs. These large differences, however, have to be interpreted with some caution, as the estimation for female workers can only be performed for a reduced sample (cf. Table A4.3, column 6, in the Appendix).

Again, predicted probabilities of self-financing training conditional on receiving no employer support are additionally calculated separately for monetary and non-monetary costs (cf. Table 4.2). This reveals interesting new insights.

Table 4.2: Predicted training probabilities conditional on receiving no employer support in respect of the considered cost component

	Workers who currently receive employer support in the considered cost component			Workers who do **not** receive employer support in the considered cost component			Mean comparison test		
	Full Sample	Male Workers	Female Workers	Full Sample	Male Workers	Female Workers	Full Sample	Male Workers	Female Workers
Monetary costs	0.2945 (0.0083)	0.3153 (0.0107)	0.2919 (0.0163)	0.1830 (0.0067)	0.2076 (0.0094)	0.1571 (0.0112)	***	***	***
Non-monetary costs	0.2392 (0.0061)	0.2321 (0.0087)	0.2593 (0.0112)	0.1433 (0.0046)	0.1441 (0.0074)	0.1438 (0.0072)	***	***	***

With regard to monetary costs, the results demonstrate that those workers whose firm currently pays (part of) the training expenses would also have a significantly higher

willingness to bear the full monetary costs had they not received any employer support. This predicted probability exceeds by more than half the probability for the group of workers who currently do not receive financial assistance. This difference is highly significant. Not surprisingly, the numbers for both groups are higher than those for the analysis using a cost measure including all types of costs (cf. Table 4.1). Some workers who do not receive financial assistance might still be supported in terms of non-monetary costs. This, however, is not the norm, as has been shown in the previous section.

Turning to the results for non-monetary costs, one notices that the predicted training probabilities conditional on receiving no employer support in terms of non-monetary costs are considerably lower than those found for monetary costs. Receiving the opportunity to undertake training during working hours is a better predictor of actual participation than receiving financial support. This indicates the importance of training opportunities during working hours. Comparing workers who receive training during working hours with those who do not, the main patterns found with respect to monetary costs remain evident. Hence, the hypothesis test is also confirmed for monetary and non-monetary costs. However, the predicted probabilities vary systematically according to the cost component examined. These differences are even more pronounced when considering male and female workers separately. Men have on average a higher willingness to bear monetary costs than do women. The difference is even higher in the group of workers who presently do not receive employer support. In contrast, women would be at least as likely as men to fully participate during leisure time.

In summary, workers' average willingness to bear the full training costs is rather low. This applies to both groups of workers analyzed but is even more pronounced in the group of those employees who are presently not considered for employer-supported training. Obviously, firms moderate practically all training decisions and thus considerably influence training (non-)participation patterns. Concerning different cost components, our findings demonstrate that there are systematic differences in the respective willingness to bear the full training costs. Workers are a lot more likely to pay for training than they are to sacrifice leisure time. Thus, non-monetary costs seem to form the more binding restriction.

Up to this point, we have not analyzed whether firms consider workers' willingness to bear training costs. This is the focus of the next section and might help to explain the observed training participation patterns.

4.5.4. Analysis of the relation of workers' and firms' training decisions

In the previous section, we have shown that those workers who receive employer-supported training would also be the ones more likely to have borne the full training costs themselves had they not received employer support. The question to be answered is why firms support some workers who would also be willing to bear the full training costs themselves. There are several explanations for this phenomenon, which will be discussed in the following.

Basically, there are two explanatory approaches, which differ in their underlying assumption on whether firms (can) consider workers' willingness to bear training costs in their training decisions. Theoretically, we expect that a firm invests in training if benefits exceed costs. Thus, we would assume that a worker's willingness to bear training costs is not incorporated in the firm's training decision. The empirical findings could also be explained by the existence of information asymmetry. In this case, firms cannot identify those workers who would also be willing to self-finance their training participation, or identification would be very costly. Both explanations predict that firms' decisions are made independently of the workers' willingness to bear the full training costs.

Alternatively, one could argue that the patterns observed are a result of firms' human resource strategies. Training either constitutes a component of a worker's compensation package or is used as a means of improving an employee's commitment to the firm. Of course firms do not know a worker's exact willingness to bear training costs, but they might have a guess about it. Thus, we expect that a worker's willingness to bear training costs is positively associated with his probability of receiving employer support because the former indicates a worker's interest in – as well as his benefit from – training.

In order to investigate which explanation approach is supported by the empirical evidence, we incorporate two variables representing a worker's willingness to bear training costs into the estimation model used to analyze a firm's training decision. On the one hand, we include a variable indicating whether a worker is willing to pay for training. On the other hand, we use a worker's statement of whether he lacks time to participate in training as a proxy for his willingness to sacrifice leisure time for training. The results are presented in Table 4.3 (for the detailed estimation results see Table A4.6 in the Appendix).

Table 4.3: Relation of training decisions

	Employer-supported training		
	Monetary and non-monetary costs	Monetary costs	Non-monetary costs
Willingness to pay	0.2267*** (0.0458)	0.1700*** (0.0432)	
Lack of time	-0.1447*** (0.0298)		-0.1399*** (0.0296)
Individual characteristics	YES	YES	YES
Employment characteristics	YES	YES	YES
Prob > χ^2	0.0000	0.0000	0.0000
N	1365	1365	1365

Notes: Marginal effects at the mean; std.errors are in parentheses; *statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

In favor of the latter approach (i.e., the commitment explanation), the variable representing a worker's willingness to pay for training turns out to have a significant positive impact on the probability of receiving employer-supported training.[63] Moreover, workers who state that they lack time for training participation are not more but actually less likely to be selected for employer-supported training. These patterns also hold when looking at monetary and non-monetary costs separately and when performing separate estimations by gender.[64] Thus, the probability of receiving employer-supported training is not independent of but rather positively associated with a worker's willingness to bear training costs.

Although the main aim of training has to be seen in increasing workers' productivity, firms seem to pursue a strategy of increasing workers' commitment to the firm by also providing employer support in training participation. Thus, they consciously accept that some of these workers would also be willing to self-finance their training. Of course, we would need more detailed information about a firm's human resource strategy in order to conclusively confirm this explanation. However, we interpret our estimation results as evidence in favor of such a relation.

Alternatively, the findings could indicate that sharing of training costs is widespread and requires that workers are willing to partly pay for training and also to participate during leisure time. However, as for two thirds of those workers who are selected for employer-supported training firms cover the full monetary and non-monetary training costs, this explanation is unlikely.

Of course, training content as well as the aim of training might systematically vary between the two groups (i.e., those workers who receive employer-supported training and those who

[63] The main results presented in section 4.5.1 still hold after introducing the two additional variables. This indicates that although other individual characteristics might be correlated with the willingness to bear training costs, this does not have an impact on their determination of the probability of employer-supported training.
[64] The results from separate estimations for male and female workers can be obtained from the authors upon request.

bear the full training costs themselves).[65] We would expect firms to predominantly support training that increases a worker's productivity within the firm, while workers who self-finance their training might generally aim at improving their labor market prospects. This, however, is not within the scope of our study but could be an interesting question for further research.

Finally, training might not only be useful for increasing employees' commitment to the firm but also for attracting new workers and thus for improving recruitment success (cf. chapter five). This explanation neither supports nor contradicts the finding presented in Table 4.3 and unfortunately cannot be tested with the current dataset, which does not provide the necessary information about a firm's vacancy rate or recruitment success.

4.6. Conclusions

We empirically examined training decisions of workers and firms, with a focus on training costs. Our analysis distinguished monetary from non-monetary costs in order to learn how various cost components affect workers' (non-)participation in training. The results show that employer support in terms of both monetary and non-monetary costs is crucial for training participation. The latter have rarely been considered in the literature to date but seem to form the main binding restrictions.

The use of an exceptionally rich dataset allowed us to identify the employer's selection process separate from the worker's willingness to bear full training costs and also allowed us to compare the importance of monetary and non-monetary costs. This yields new insights into non-participation patterns in particular. Interestingly, the findings show that the (predicted) probability of self-financing training participation is generally low but that it is higher for those presently receiving employer-supported training. Aside from this, the prevalence of employer-supported training found in previous studies is confirmed. Obviously, firms moderate virtually all training decisions. Accordingly, policies aiming at increasing training participation should consider firms' incentives for providing training.

Looking at monetary and non-monetary cost components separately, the main patterns remain evident: non-participation can be attributed to a lower willingness (or ability) of these workers to bear full training costs, as well as to a lack of employer support in terms of both monetary and non-monetary costs. However, non-monetary costs have rarely been considered (separately) in the literature but seem to form the binding restriction. The question to be

[65] For instance, Pischke (2001) provides some evidence that training during leisure time is associated with more pronounced wage growth than is training during working hours (though the effect is not significant).

answered, then, is why firms do not provide more support in terms of non-monetary costs. One explanation for firms providing financial assistance over training during working hours is that the latter might result in overtime, which is more costly for the company than is covering training expenses. Another probable explanation is that in small firms, for instance, in which the production process is dependent on every single worker, participation during working hours might simply be impossible (as this would result in production loss). Nevertheless, support for a worker's training participation during leisure time might be possible.

Alternatively, one could argue that firms just do not know about the existence of time restrictions. This, however, does not seem to be the case. Quite the contrary: workers' willingness to bear training costs is positively associated with receiving employer support in training participation. We assume that firms thereby pursue a strategy of increasing workers' commitment to the firm. Thus, the observed relation is rather the result of conscious decisions made by firms than the result of allocation problems concerning training support within firms.

Of course, the final responsibility of participating in training rests on the individual worker. Nevertheless, a society should aim at having an educational and further training system that ensures a productive populace. It would therefore be interesting to combine an analysis of different benefits with an examination of the various cost components and thereby evaluate firms' incentives to provide training. This may be an issue for future research, assuming the existence of an appropriate dataset. Until then, one should keep in mind that, for both the worker and the firm, time seems to be more costly than money.

In the next chapter we will study whether companies have different types of benefits if they train workers, i.e., direct productivity increasing effects and indirect effects such as positive reputation effects and better recruitment opportunities.

Appendix

Table A4.1: Types of training included

NAME OF CATEGORY	TYPES OF TRAINING REPORTED IN THE SURVEY
Self-organized cvt	Self-organized continuing vocational training: distance learning course computer based learning self-organized learning using TV, radio or video self-organized learning using textbooks, teaching material or technical literature
Training program (cvt inst./school)	Seminar, course, training at a continuing vocational training institute at a technical school continuing vocational training in the scientific domain
Congress, conference	Technical lecture, congress, conference, trade fair
Training program (company)	Seminar, course, training at the (own) company, at a manufacturer, at a supplier
Job-integrated learning	Types of further qualifications that are closely related to job organized initial skill adaptation training or instruction at the workplace, trainee-program operational activities to increase occupational qualification operational exchange activities (e.g. with another company) activities of occupational orientation

Table A4.2: Definitions and descriptives of variables

Variable	Definition	Mean (Std.dev.)			
		Full Sample		Participants	
		Non-participants	Participants	Employer-supported	Self-financed
DEPENDENT VARIABLE					
Employer-supported training	1 if firm covers (part of) worker's training costs, 0 otherwise	0.5267 (0.4995)			
Self-financed training	1 if worker bears full training costs (cond. on receiving **no** employer-supported training), 0 otherwise	0.0759 (0.2650)			
INDEPENDENT VARIABLE					
Individual Characteristics					
No educational degree	Reference	0.0553 (0.2287)	0.0234 (0.1514)	0.0195 (0.1383)	0.0816 (0.2766)
Secondary education		0.8208 (0.3839)	0.5872 (0.4927)	0.6022 (0.4898)	0.3673 (0.4871)
Tertiary education		0.1240 (0.3298)	0.3893 (0.4879)	0.3783 (0.4853)	0.5510 (0.5025)
Male	1 if a person is male, 0 otherwise	0.5176 (0.5001)	0.5885 (0.4924)	0.5855 (0.4930)	0.6327 (0.7871)
Child	1 if a person has at least one child, 0 otherwise	0.4489 (0.4978)	0.4453 (0.4973)	0.4506 (0.4979)	0.3673 (0.4871)
Age25_34	Reference	0.2563 (0.4369)	0.2526 (0.4348)	0.2448 (0.4303)	0.3673 (0.4871)
Age35_44		0.3652 (0.4819)	0.4115 (0.4924)	0.4103 (0.4922)	0.4286 (0.5000)
Age45_54		0.2781 (0.4484)	0.2630 (0.4406)	0.2726 (0.4456)	0.1224 (0.3312)
Age55_64		0.1005 (0.3010)	0.0729 (0.2602)	0.0723 (0.2592)	0.0816 (0.2766)
Part-time employment	1 if a person is employed part-time, 0 if a person is employed full-time	0.2563 (0.4369)	0.1641 (0.3706)	0.1599 (0.3668)	0.2245 (0.4216)
Motivation	1 if training and learning is fun	0.7990 (0.4011)	0.9440 (0.2301)	0.9458 (0.2267)	0.9184 (0.2766)
Willingness to pay	1 if willingness to pay in Euro >0, 0 otherwise	0.7822 (0.4131)	0.9466 (0.2249)	0.9430 (0.2920)	
Lack of time	1 if there is lack of time for training participation, 0 otherwise	0.5477 (0.4981)	0.3646 (0.4816)	0.3602 (0.4804)	
Employment Characteristics					
White-collar worker	1 if a person is a white-collar worker, 0 if a person is a blue-collar worker	0.6030 (0.4897)	0.8555 (0.3519)	0.8554 (0.3520)	0.8571 (0.3536)
Change	1 if knowledge and skill needs change, 0 otherwise	0.4874 (0.5003)	0.7122 (0.4530)	0.7177 (0.4504)	0.6327 (0.4871)
Experience (divided by 10)	Labor market experience (in 10 years)	2.3774 (1.0136)	2.1085 (1.0119)	2.1314 (1.0054)	1.7714 (1.0559)
Micro enterprise	<10 employees, Reference	0.1910 (0.3934)	0.0977 (0.2970)	0.0904 (0.2870)	0.2041 (0.4072)
Small&medium-sized enterprise	10-249 employees	0.4204 (0.4940)	0.3372 (0.4731)	0.3338 (0.4719)	0.3878 (0.4923)
Large enterprise	>249 employees	0.3886 (0.4878)	0.5651 (0.4961)	0.5758 (0.4946)	0.4082 (0.4966)
Primary sector of industry	Reference	0.1457 (0.3531)	0.0755 (0.2644)	0.0751 (0.2637)	0.0816 (0.2766)
Secondary sector of industry		0.3082 (0.4621)	0.2734 (0.4460)	0.2726 (0.4456)	0.2857 (0.4564)
Tertiary sector of industry		0.5461 (0.4983)	0.6510 (0.4770)	0.6523 (0.4766)	0.6327 (0.4871)
Instrumental variable					
Fraction of training by industry	Fraction of employer-supported training by industry code	0.4794 (0.1138)	0.5370 (0.1159)	0.5387 (0.1167)	

Note: The firm size categories are according to the EU-definition.

Table A4.3: Employer-supported and self-financed training: including all types of costs

	Employer-supported training			Self-financed training		
	Full Sample	Male Workers	Female Workers	Full Sample	Male Workers	Female Workers°
Individual characteristics						
No educational degree	Reference	Reference	Reference	Reference	Reference	Reference
Secondary education	0.1839**	0.2740**	0.1228	-0.0453	-0.1002	0.025
	(0.0758)	(0.1099)	(0.1073)	(0.0403)	(0.0635)	(0.0456)
Tertiary education	0.3030***	0.3445***	0.3110***	0.104	0.0396	0.2059
	(0.0811)	(0.1155)	(0.1175)	(0.0852)	(0.0948)	(0.2824)
Male	0.0528			0.0206		
	(0.0361)			(0.0168)		
Child	-0.0094	0.0461	-0.1040*	-0.0283*	-0.0204	-0.0433
	(0.0328)	(0.0416)	(0.0547)	(0.0163)	(0.0194)	(0.0379)
Age25_34	-0.2343**	-0.0955	-0.3666***	-0.0852*	-0.0658	-0.5967***
	(0.1038)	(0.1472)	(0.1387)	(0.0478)	(0.0809)	(0.1320)
Age35_44	-0.0811	0.01	-0.1327	-0.0537	-0.0399	-0.5328***
	(0.0946)	(0.1278)	(0.1380)	(0.0656)	(0.1065)	(0.2048)
Age45_54	0.0024	0.0826	-0.085	-0.0644*	-0.0393	-0.4951***
	(0.0716)	(0.0960)	(0.1082)	(0.0371)	(0.0701)	(0.1245)
Age55_64	Reference	Reference	Reference	Reference	Reference	Reference
Part-time employment	-0.1392***	-0.1484	-0.1214**	0.0088	0.0297	-0.0093
	(0.0422)	(0.1159)	(0.0505)	(0.0226)	(0.0529)	(0.0369)
Motivation	0.2467***	0.2543***	0.2521***	0.0249*	0.0043	
	(0.0437)	(0.0581)	(0.0648)	(0.0151)	(0.0242)	
Employment characteristics						
White-collar worker	0.2325***	0.2768***	0.2217***	0.0358**	0.0324	
	(0.0371)	(0.0453)	(0.0658)	(0.0155)	(0.0236)	
Change	0.1501***	0.1447***	0.1648***	0.0209	0.0416*	0.0013
	(0.0300)	(0.0409)	(0.0448)	(0.0157)	(0.0235)	(0.0280)
Experience (divided by 10)	-0.0591	-0.125	0.016	-0.0458	-0.0192	-0.1063**
	(0.0776)	(0.0976)	(0.1281)	(0.0319)	(0.0475)	(0.0537)
Experience squared	-0.0011	0.001	-0.0032	0.0002	-0.0006	0.0003
	(0.0017)	(0.0021)	(0.0027)	(0.0007)	(0.0012)	(0.0012)
Micro enterprise	Reference	Reference	Reference	Reference	Reference	Reference
Small and medium-sized enterprise	0.0914**	0.065	0.1093*	-0.0305	-0.1155**	0.038
	(0.0454)	(0.0687)	(0.0621)	(0.0246)	(0.0450)	(0.0379)
Large enterprise	0.1874***	0.1365*	0.2408***	-0.0394*	-0.1228***	0.02
	(0.0456)	(0.0697)	(0.0618)	(0.0226)	(0.0434)	(0.0376)
Primary sector of industry	0.0855	0.0255	0.2153*	-0.0202	-0.0534**	0.0577
	(0.0549)	(0.0641)	(0.1143)	(0.0215)	(0.0231)	(0.1129)
Secondary sector of industry	Reference	Reference	Reference	Reference	Reference	Reference
Tertiary sector of industry	0.0074	-0.0648	0.1469**	-0.0077	-0.0349	0.0407
	(0.0365)	(0.0459)	(0.0605)	(0.0198)	(0.0266)	(0.0265)
Fraction of training by industry	0.7191***	0.6562***	0.7511***			
	(0.1509)	(0.2167)	(0.2119)			
Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
N	1365	761	604	646	340	203

Notes: Marginal effects at the mean; std.errors are in parentheses; *statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level; ° Low motivation as well as being a blue-collar worker predicts failure perfectly for which reason those workers are not included in the respective estimation.

Table A4.4: Employer-supported and self-financed training: monetary costs

	Employer-supported training			Self-financed training		
	Full Sample	Male Workers	Female Workers	Full Sample	Male Workers	Female Workers
Individual characteristics						
No educational degree	Reference	Reference	Reference	Reference	Reference	Reference
Secondary education	0.1353*	0.1716	0.1262	-0.0068	-0.0146	0.0005
	(0.0744)	(0.1089)	(0.1052)	(0.0571)	(0.0791)	(0.0658)
Tertiary education	0.2029**	0.2299**	0.1933	0.2301**	0.1705	0.2886
	(0.0828)	(0.1161)	(0.1249)	(0.1060)	(0.1238)	(0.1952)
Male	0.0302			0.0414		
	(0.0350)			(0.0304)		
Child	0.0045	0.0361	-0.0466	-0.0543*	-0.0172	-0.0717**
	(0.0320)	(0.0412)	(0.0526)	(0.0295)	(0.0405)	(0.0346)
Age25_34	-0.2879***	-0.1173	-0.4355***	-0.0299	0.0608	-0.2196***
	(0.1003)	(0.1445)	(0.1314)	(0.0701)	(0.1142)	(0.0671)
Age35_44	-0.1798*	-0.0541	-0.2626*	0.0633	0.1482	-0.1176
	(0.0946)	(0.1291)	(0.1370)	(0.0926)	(0.1382)	(0.1377)
Age45_54	-0.0985	-0.0022	-0.1797	0.0747	0.1672	-0.1112
	(0.0743)	(0.1009)	(0.1095)	(0.0736)	(0.1168)	(0.0956)
Age55_64	Reference	Reference	Reference	Reference	Reference	Reference
Part-time employment	-0.1437***	-0.1489	-0.1383***	-0.0209	0.0298	-0.0349
	(0.0403)	(0.1114)	(0.0483)	(0.0353)	(0.0962)	(0.0331)
Motivation	0.2479***	0.2467***	0.2514***	0.0710**	0.0684	0.0655**
	(0.0402)	(0.0544)	(0.0584)	(0.0302)	(0.0438)	(0.0283)
Employment characteristics						
White-collar worker	0.2270***	0.2649***	0.1918***	0.0929***	0.1095**	0.1094***
	(0.0355)	(0.0445)	(0.0630)	(0.0280)	(0.0435)	(0.0248)
Change	0.1150***	0.1133***	0.1227***	0.0894***	0.1126***	0.0553*
	(0.0296)	(0.0406)	(0.0436)	(0.0270)	(0.0391)	(0.0314)
Experience (divided by 10)	0.0824	0.0377	0.119	-0.2006***	-0.2406**	-0.1619**
	(0.0742)	(0.0953)	(0.1161)	(0.0652)	(0.0959)	(0.0785)
Experience squared	-0.0036**	-0.0017	-0.0053**	0.0027*	0.0034	0.0017
	(0.0016)	(0.0021)	(0.0025)	(0.0014)	(0.0023)	(0.0015)
Micro enterprise	Reference	Reference	Reference	Reference	Reference	Reference
Small and medium-sized enterprise	0.0792*	0.0749	0.0947	-0.0002	-0.0919	0.036
	(0.0443)	(0.0671)	(0.0594)	(0.0390)	(0.0647)	(0.0358)
Large enterprise	0.1758***	0.1707**	0.1928***	0.0087	-0.1053	0.0710*
	(0.0453)	(0.0690)	(0.0609)	(0.0401)	(0.0665)	(0.0405)
Primary sector of industry	0.0637	0.0213	0.1789	0.0122	-0.0619	0.062
	(0.0568)	(0.0669)	(0.1166)	(0.0496)	(0.0576)	(0.0855)
Secondary sector of industry	Reference	Reference	Reference	Reference	Reference	Reference
Tertiary sector of industry	-0.0044	-0.0593	0.1057*	0.0249	-0.046	0.0964***
	(0.0352)	(0.0447)	(0.0574)	(0.0316)	(0.0466)	(0.0297)
Fraction of training by industry	0.6422***	0.5446**	0.7185***			
	(0.1762)	(0.2497)	(0.2463)			
Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
N	1365	761	604	731	390	341

Notes: Marginal effects at the mean; std.errors are in parentheses; *statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table A4.5: Employer-supported and self-financed training: non-monetary costs

	Employer-supported training			Self-financed training		
	Full Sample	Male Workers	Female Workers	Full Sample	Male Workers	Female Workers
Individual characteristics						
No educational degree	Reference	Reference	Reference	Reference	Reference	Reference
Secondary education	0.1590**	0.2482**	0.0808	-0.0141	-0.0912	0.0639
	(0.0761)	(0.1102)	(0.1093)	(0.0515)	(0.0828)	(0.0522)
Tertiary education	0.2753***	0.3049***	0.3002**	0.1701*	0.1042	0.2064
	(0.0837)	(0.1177)	(0.1238)	(0.0975)	(0.1251)	(0.1643)
Male	0.0719**			0.0018		
	(0.0359)			(0.0293)		
Child	-0.0104	0.0513	-0.1007*	-0.0377	-0.0202	-0.0649
	(0.0328)	(0.0419)	(0.0535)	(0.0272)	(0.0336)	(0.0443)
Age25_34	-0.2365**	-0.0229	-0.4457***	-0.0779	-0.1327	-0.1312
	(0.1048)	(0.1499)	(0.1265)	(0.0663)	(0.1001)	(0.0815)
Age35_44	-0.0954	0.0742	-0.2417*	0.0013	-0.0825	0.0078
	(0.0992)	(0.1317)	(0.1384)	(0.0877)	(0.1225)	(0.1502)
Age45_54	-0.0061	0.1038	-0.1317	-0.0015	0.0024	-0.0721
	(0.0762)	(0.1018)	(0.1105)	(0.0643)	(0.1129)	(0.0869)
Age55_64	Reference	Reference	Reference	Reference	Reference	Reference
Part-time employment	-0.1440***	-0.1714	-0.1253**	-0.0002	0.0245	0.0078
	(0.0413)	(0.1113)	(0.0493)	(0.0335)	(0.0825)	(0.0417)
Motivation	0.2212***	0.2133***	0.2490***	0.0830***	0.0763**	0.0796**
	(0.0434)	(0.0588)	(0.0621)	(0.0247)	(0.0316)	(0.0353)
Employment characteristics						
White-collar worker	0.2452***	0.2975***	0.2325***	0.0504*	0.0341	0.0652*
	(0.0359)	(0.0447)	(0.0606)	(0.0281)	(0.0382)	(0.0390)
Change	0.1510***	0.1525***	0.1509***	0.0511**	0.0612*	0.0604*
	(0.0299)	(0.0409)	(0.0442)	(0.0242)	(0.0330)	(0.0333)
Experience (divided by 10)	-0.0446	-0.1471	0.0813	-0.1219**	-0.0882	-0.1778**
	(0.0777)	(0.0986)	(0.1268)	(0.0616)	(0.0854)	(0.0808)
Experience squared	-0.0014	0.0016	-0.0047*	0.0014	0.0004	0.0022
	(0.0017)	(0.0021)	(0.0027)	(0.0013)	(0.0019)	(0.0017)
Micro enterprise	Reference	Reference	Reference	Reference	Reference	Reference
Small and medium-sized enterprise	0.0963**	0.1014	0.0908	-0.0181	-0.1363**	0.0581
	(0.0448)	(0.0691)	(0.0601)	(0.0366)	(0.0614)	(0.0437)
Large enterprise	0.2099***	0.2050***	0.2279***	-0.0396	-0.1856***	0.067
	(0.0454)	(0.0700)	(0.0613)	(0.0350)	(0.0533)	(0.0461)
Primary sector of industry	0.0898	0.0262	0.1904	0.0111	-0.0388	0.1315
	(0.0572)	(0.0664)	(0.1256)	(0.0403)	(0.0405)	(0.1080)
Secondary sector of industry	Reference	Reference	Reference	Reference	Reference	Reference
Tertiary sector of industry	-0.0046	-0.0774*	0.1314**	0.0412	0.0155	0.0801**
	(0.0361)	(0.0453)	(0.0591)	(0.0302)	(0.0423)	(0.0361)
Fraction of training by industry	0.7510***	0.5869***	0.8502***			
	(0.1475)	(0.2072)	(0.2087)			
Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002
N	1365	761	604	697	361	336

Notes: Marginal effects at the mean; std.errors are in parentheses; *statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

Table A4.6: Relation of training decisions

	Employer-supported training		
	Monetary & non-monetary costs	Monetary costs	Non-monetary costs
Individual characteristics			
No educational degree	Reference	Reference	Reference
Secondary education	0.1853**	0.1245	0.1732**
	(0.0796)	(0.0760)	(0.0769)
Tertiary education	0.2833***	0.1848**	0.2769***
	(0.0858)	(0.0841)	(0.0855)
Male	0.0528	0.0291	0.0724**
	(0.0367)	(0.0353)	(0.0360)
Child	0.0097	0.0084	0.0047
	(0.0335)	(0.0321)	(0.0333)
Age25_34	-0.2636**	-0.3024***	-0.2488**
	(0.1072)	(0.1012)	(0.1061)
Age35_44	-0.1235	-0.1985**	-0.1152
	(0.0976)	(0.0953)	(0.1002)
Age45_54	-0.0371	-0.113	-0.0289
	(0.0739)	(0.0749)	(0.0773)
Age55_64	Reference	Reference	Reference
Part-time employment	-0.1454***	-0.1454***	-0.1478***
	(0.0425)	(0.0403)	(0.0414)
Motivation	0.2160***	0.2296***	0.2152***
	(0.0467)	(0.0421)	(0.0441)
Willingness to pay	0.2267***	0.1700***	
	(0.0458)	(0.0432)	
Lack of time	-0.1447***		-0.1399***
	(0.0298)		(0.0296)
Employment characteristics			
White-collar worker	0.2180***	0.2171***	0.2436***
	(0.0381)	(0.0359)	(0.0361)
Change	0.1502***	0.1143***	0.1511***
	(0.0305)	(0.0297)	(0.0302)
Experience (divided by 10)	-0.0339	0.0831	-0.0239
	(0.0787)	(0.0742)	(0.0786)
Experience squared	-0.0015	-0.0036**	-0.0019
	(0.0017)	(0.0016)	(0.0017)
Micro enterprise	Reference	Reference	Reference
Small and medium-sized enterprise	0.0976**	0.0797*	0.1001**
	(0.0461)	(0.0444)	(0.0450)
Large enterprise	0.1808***	0.1723***	0.2076***
	(0.0461)	(0.0452)	(0.0455)
Primary sector of industry	0.0744	0.0608	0.079
	(0.0557)	(0.0568)	(0.0577)
Secondary sector of industry	Reference	Reference	Reference
Tertiary sector of industry	0.0007	-0.0062	-0.0107
	(0.0369)	(0.0354)	(0.0361)
Fraction of training by industry	0.6911***	0.6443***	0.7082***
	(0.1510)	(0.1756)	(0.1474)
Prob > χ^2	0.0000	0.0000	0.0000
N	1365	1365	1365

Notes: Marginal effects at the mean; std.errors are in parentheses; *statistically significant at the 0.10 level, **at the 0.05 level, ***at the 0.01 level.

CHAPTER 5

Avoiding Labor Shortages Through Employer Signaling

On the Importance of Good Work Atmosphere and Labor Relations

in: *Industrial and Labor Relations Review*, forthcoming (2010) (with Uschi Backes-Gellner)

5.1. Introduction

Avoiding labor shortages or job vacancies is a key factor in the competiveness of firms, particularly in innovative, high quality or labor intensive industries. However, job vacancy rates and how to avoid vacancies has hardly been studied in the past neither theoretically nor empirically. We propose a novel theoretical analysis to study how employers may gain a competitive advantage in reducing labor shortage. We call it *employer* signaling,[66] which is the reverse of *employee* signaling as introduced by Spence (1973). We test the implications of our theoretical analysis by using a unique company data set, which covers a large number of variables on companies' workplace characteristics and we provide innovative and far-reaching results. We find that companies are clearly able to reduce job vacancies by signaling the quality of their labor relations through a number of observable company characteristics. These characteristics have so far not been regarded in direct relation to recruitment success and avoiding high job vacancy rates. Works councils, the analogue of the workplace union in

[66] The existence of employer signaling towards other markets such as the capital market and also the labor market is demonstrated by Backes-Gellner/Werner (2007). They show that newly founded firms signal the quality of their firm to banks and potential employees via educational signals from the founder.

other countries, for example have been extensively analyzed with respect to worker productivity, investment issues, or the well-being of *incumbent* workers (see e.g. Addison et al. 2007 or Addison et al. 2004). But their value to *potential* employees and their *in*direct effects on productivity via improved recruitment success have not been studied so far. Similarly, and to take a second example, apprenticeship training has been studied innumerable times with respect to earnings, productivity or skill shortage prevention through skill enhancement. But its *in*direct effect on avoiding job vacancies via improved *recruitment* success from the external workforce has not been recognized so far, nor has it been empirically studied.[67] We find that the existence of an apprenticeship training program significantly enhances the *recruitment* of skilled employees and thereby has a double effect on avoiding high job vacancy rates: internal upgrading of skills (which is what has been studied in the past) and external skill acquisition (which is what we introduce and study here). Thus it seems that companies do not have a choice to either invest in training *or* to poach skilled workers on the external labor market, rather the choice is to invest in training *and* thereby also increase chances of recruiting externally skilled workers, or not to invest in training *and* additionally decrease chances of recruiting externally. Thus, a poaching strategy seems particularly dangerous in tight labor markets because our empirical results also show that just offering higher wages than competitors will usually not be sufficient. Our results indicate that a deeper analysis of employer signaling, recruitment success and avoidance of job vacancies is an interesting field for future research with a potential for far-reaching theoretical and empirical implications.

5.2. Inter-firm differences in job vacancy rates: the empirical phenomenon

Skill shortages and job vacancies are a widespread problem occurring whenever the current number of workers with particular skills is lower than the number of jobs requiring these skills. Given any such skill shortage on the labor market, one of the major challenges for each individual firm is to fill its own job openings by attracting relatively more workers than others to gain a competitive advantage. And indeed, we observe empirically that the ability to fill job vacancies is not at all evenly distributed among firms. Despite severe labor shortages on an aggregate level there are substantial and stable variations across firms on a disaggregated level, including firms without any job vacancies at all (see e.g. Holzer 1994 or Morissette/Zhang 2001). However, there has been a notable lack of theoretical or empirical

[67] A notable exception is Sadowski (1980), who even then argued that there is a reputation effect to training which should make it easier for firms to hire from the external labor market.

work investigating such inter-firm differences in job vacancy rates. Micro- or firm-level empirical analyses of job vacancy rates and their determinants were, to the best of our knowledge, non-existent before our studies.

One rather obvious economic explanation for inter-firm differences in job vacancies could be mismatches between the skill requirements of single firms and the skills available in the external workforce. However, empirical results do not seem to support such an explanation: differences in inter-firm job vacancy rates are still large when differences in skill requirements are controlled for, as has been shown for example by Backes-Gellner et al. (2006).[68] Another rather simple economic explanation could be that differences in job vacancy rates are due to inter-firm wage differentials. But here again the data do not seem to support the hypothesis. Job vacancies are not only observed in low wage firms but also, and to a similar extent, in high wage firms, as has been shown by Schmidtke/Backes-Gellner (2002). Higher wages alone obviously do not solve the problem, at least not during the tight labor market phase of the late 1990s in Germany, the period covered by our data. These results are compatible with what Dey/Flinn (2005) find for the US, although they did not directly study job vacancy but job mobility rates. In their model, firms' health insurance decisions are taken in a cooperative manner, recognizing the productivity effects of health insurance and its nonmonetary value to the employee. The resulting equilibrium is one in which not all employment matches are covered by health insurance, wages for jobs providing health insurance are higher than those for jobs without health insurance, and workers at jobs with health insurance are less likely to leave those jobs even after conditioning on the wage rate. Dey/Flinn's (2005) argument that health insurance has an additional non-pecuniary value is similar to what we argue in our employer signaling model, which deals with other workplace characteristics that also have an additional non-monetary value. However, Dey/Flinn (2005) were not studying inter-firm differences in job vacancy rates.

To summarize, the question as to why some firms are able to fill their job openings despite an aggregate labor shortage and other firms are not remains unanswered to date. In this chapter we will study what characterizes one type of firm or another. We focus on the impact of work atmosphere and labor relations. As already mentioned, our basic assumption is that the ability to fill job openings does not exclusively depend on monetary issues such as wages or fringe benefits. We argue, rather, that company or job characteristics fostering individual workplace satisfaction have key additional value because they may provide important comparative

[68] This is in line with the study of Morrisette/Zhang (2001) showing that there are at least two types of establishments with high job vacancy rates: those with fairly high skill requirements and those in high turnover, low-paid, non-unionized sectors such as retail trade and consumer services industries.

advantages in the recruitment process. We concentrate on *external* recruitment in our study and control for differences in the number of job openings that may result from differences in internal staffing and recruitment success.[69]

5.3. Non-observable workplace characteristics as a recruitment-problem and employer signaling as a solution

If we assume that not all of the job characteristics preferred by workers are directly observable to a job *applicant*, but may only become apparent after they have worked for some time, firms with high quality workplaces have a problem in reliably communicating their superior quality. Moreover, workers face a considerable risk in their job decision because if they accept a job without reliable information on non-observable qualities, the decision may become quite expensive for them. Before they find out about the true quality, they may have turned down other job alternatives and may have invested in firm-specific 'human capital', including for example moving to a new location, which makes it difficult or costly to reverse the original job decision. Workers should therefore be interested in finding reliable means to reduce their risk. We argue that job applicants, like any other economic agent in any other market with asymmetric information, use signals to reduce the risk resulting from such asymmetric information.

We use Spence's theory of labor market signaling (1973) and reverse it to explain inter-firm differences in recruitment success. We argue that it is not only employees, as suggested by Spence, but also employers who, by means of their observable characteristics, signal their non-observable quality. Thus, job applicants prefer to work in firms that send such signals, even if an observable characteristic seems to be of no *direct* interest to the applicant. For example, it may seem irrelevant for a skilled craftsman who has already finished his apprenticeship training that a company maintains an apprenticeship program, because he himself no longer needs an apprenticeship. However, the existence of an apprenticeship program may - as a signal - still be relevant to a skilled craftsman applying for a job, because it serves as a reliable signal for other job characteristics the worker values but cannot readily observe. Such highly valued characteristics are for example a firm's orientation towards quality work, its innovativeness or long-term orientation and career prospects. Another example of a signal may be the existence of a works council. So far, works councils have been extensively analyzed with respect to their impact on the *incumbent* workforce (e.g. Addison et

[69] For a systematic comparison of internal vs. external recruitment options, see e.g. Bayo-Moriones/Ortín-Ángel (2006).

al. 2007; Sako/Jackson 2006; Heywood/Jirjahn 2002; Bellmann/Blien 2001). Within our framework, we argue that there is a second and probably similarly important effect of a works council; namely, its signaling effect to *potential* employees. The mere existence of works councils may increase the attractiveness to potential employees and thereby strongly improve recruitment success. But what could it be that a works council signals to a job applicant he can otherwise not observe? Works councils may signal higher job security or a work ethos that is particularly attractive to a skilled worker.[70] In the same way, other HR practices and labor relations issues may serve as valuable signals of a good work atmosphere and thereby help reduce job vacancies and labor shortages. But an observable characteristic has to meet a few requirements in order to become a valid signal, which is what we will tackle in the following section.

5.4. Employer signaling: theoretical analysis

Like Spence, we start with assuming that prior to accepting a job offer prospective employees cannot directly observe all preferred job or company characteristics (they may be non-observable or else not verifiable with tolerable costs). At the same time, there are a variety of company characteristics that are readily observable. The key question then is which of the observable characteristics can be used as reliable signals for the non-observable workplace quality. In the original *employee* signaling model, Spence derives conditions which have to be met to render an individual characteristic a *reliable* signal. We apply his analysis to employer signaling to derive two conditions for reliable *employer* signaling.

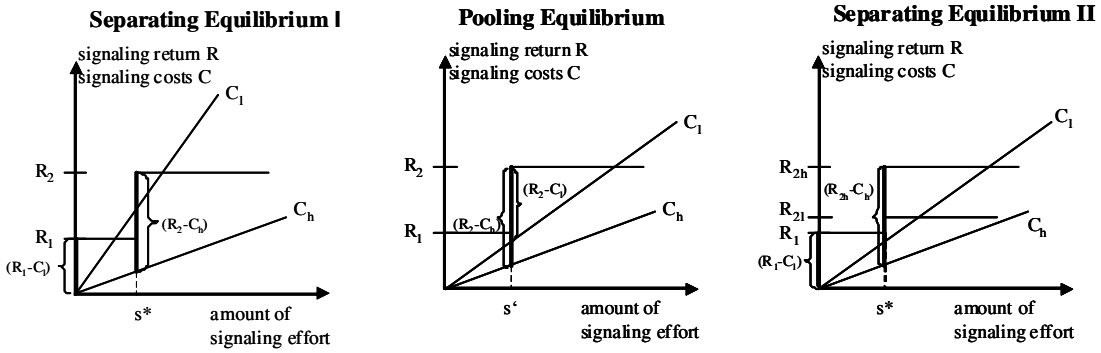
Assuming that the marginal product of employees with certain signals equals the wages paid for these signals, potential employees are, according to Spence's original model, confronted with higher or lower wages depending on whether they hold a signal or not. Signals are in general alterable, but there are costs attached. Employees in the original model only invest in a signal (a higher or lower educational level in Spence's original model), if the wage gains attached to the signal exceed their individual costs of acquiring this signal.

Accordingly, we assume in our model that *employers* signal their non-observable job quality to potential employees by observable company characteristics; however establishing these company characteristics also comes with a cost. Therefore companies only invest in a signal if

[70] Note that according to Spence (1973: 368) an observable characteristic may also have a direct value in addition to the signaling value. As long as the direct value does not cover the full costs of producing the signal, an observable characteristic may still function as a signal (for more information see the theoretical section of this chapter).

their recruitment gains exceed their costs. To be sure that an acquired characteristic is a *reliable* signal and not just cheap talk or a marketing trick, signaling costs have to be sufficiently negatively correlated with the non-observable quality (Spence 1973: 358-59) – in our case with the preferred workplace attribute. This can be demonstrated by a diagram that is well known from Ehrenberg/Smith (2003: 293). We have adapted the diagram in panel 1, 2, and 3 of Figure 5.1 to make it fit the problem of employer signaling.

Figure 5.1: Separating and pooling equilibria



The costs for employers with highly attractive jobs to produce a signal for attractiveness are defined by C_h; the costs for employers with low or unattractive jobs by C_l. The returns are R_2 for employers who acquire the signal, or else R_1. Returns in our case are defined in terms of increased competitiveness through improved recruitment success. Given the particular cost and return structure in diagram 1, there will be a separating equilibrium because the net return (R-C) for highly productive employers is largest if they acquire the signal ($[R_2(s^*)-C_h(s^*)] > [R_1(0)-C_h(0)]$), and the net returns (R-C) for less productive employers are highest if they do not acquire the signal ($[R_1(0)-C_l(0)] > [R_2(s^*)-C_l(s^*)]$). In the second panel, however, costs are not sufficiently negatively correlated with productivity. The costs for employers with unattractive jobs to produce a signal for attractiveness are much lower in this panel, so that now their net return is highest if they acquire the better signal ($[R_2(s')-C_l(s')] > [R_1(0)-C_l(0)]$). Since nothing has changed for employers with highly attractive jobs, they still also choose to acquire the better signal ($[R_2(s')-C_h(s')] > [R_1(0)-C_h(0)]$). The result is a pooling equilibrium in which employers with good or bad jobs are not separated by the signal. These are the two situations which are distinguished in the original Spence model.

We further argue that a separating equilibrium can in addition also occur if there are sufficient differences in *returns,* which is demonstrated in panel 3. Returns for employers with highly attractive workplaces (R_{2h}) are now higher than returns for employers with low quality workplaces (R_{2l}), but costs are not different. However, the market result is the same as in

panel 1: *net* returns for employers with attractive workplaces are largest if they acquire the signal ($[R_{2h}(s^*)-C_h(s^*)] > [R_1(0)-C_h(0)]$), and *net* returns for low quality employers with unattractive workplaces are highest if they do not acquire the signal ($[R_1(0)-C_l(0)] > [R_{2l}(s^*)-C_l(s^*)]$). Thus, despite rather small or no differences in the cost structure, a separating equilibrium may still evolve if the return structures differ substantially. But how can returns be different for employers with good or bad workplaces? One possibility is that workers are more motivated in a truly attractive workplace with a good work atmosphere. As a consequence workers are likely to be more productive for firms with attractive workplaces and returns to recruiting an additional worker are higher for such firms. We will discuss other situations below in the application section.

Another condition for an observable company characteristic to become a valid signal is that it is closely related to the preferred (but non-observable) job characteristics of (potential) employees. For our analysis of employer signaling this means that if employee preferences differ, the signals they care about also differ. Thus, an observable employer characteristic may be a signal with respect to some types of workers but not to others. Therefore, to test our employer signaling idea we need information on the job attributes that particular groups of employees care about.

A large number of studies in social psychology or in the human resources management literature provide information on job attributes workers find attractive and satisfying (for a brief overview cf. Boswell et al. 2003). They show substantial differences in preferences between different groups of workers, which we will get back to later, and they find one universal result, i.e. the overwhelming importance of soft characteristics, such as work atmosphere, participation, corporate culture, career perspectives, personal development or challenging tasks. Thus, soft characteristics can be assumed to be as important as e.g. wages or classic fringe benefits for workers deciding on a job offer (cf. Boswell et al. 2003). However, these soft characteristics are usually non-observable for potential employees, and so, as suggested earlier, workers are indeed in a situation of asymmetric information and have to find a way to obtain credible information before they make their job decision.

In addition to such universally preferred soft characteristics there are other job characteristics for which preferences differ substantially between different groups of workers. According to previous studies of workers' job preferences, it is firstly important to distinguish between blue and white-collar workers because those two groups differ significantly in a large number of preferred job attributes (cf. Gruber et al. 1993). A second distinction should be made according to skill level (or hierarchical level) because higher or lower skill level employees

also differ substantially in their preferences for certain job attributes (cf. Schmidtke 2002). Accordingly, an analysis of employer signaling should distinguish four groups of employees: "unskilled/semi-skilled blue-collar workers", "skilled blue-collar workers", "skilled white-collar workers" and "managerial staff" – a distinction which is consistent with the recruiting divisions observed in many human resources departments, which implicitly confirms the relevance of this categorization. Due to data availability and space limitations we focus in this study on the second group, i.e. skilled blue-collar workers, which is also the group where labor shortages were most severe in the sample companies in the time period in question.
In what follows we first identify the job preferences and workplace attributes skilled blue-collar workers consider to be important. In a second step we introduce a set of observable company characteristics which we argue may serve as a signal for the preferred yet unobserved workplace attributes.

5.4.1. Job preferences of skilled blue-collar workers

For Germany, which is where our company data come from, Schmidtke/Backes-Gellner (2002) analyze the impact of different company and job characteristics on job satisfaction using the 12th wave of the German Socio-Economic Panel. They use ordered probit estimates to study the determinants of job satisfaction and find a good work atmosphere, challenging or interesting tasks, career prospects, job security, and net wages to be highly valued by skilled blue-collar workers (however, they find no clear preferences for fringe benefits, autonomous workplaces or performance evaluation). At the same time longer regular weekly working hours have a negative impact on job satisfaction. Similar results were found by Sousa-Poza/Sousa-Poza (2000) in a large cross-national analysis including Western European countries (incl. Germany) and Anglo-Saxon countries like the United States. They find an interesting job as well as good relations with management (a measure of work atmosphere) to be the two most important determinants of job satisfaction across all countries. Job security, career prospects and high income also have a significant positive impact. These findings are further supported by Gaertner (1999), using data from the U.S., Korea and Kenya. Accordingly, we concentrate on four job attributes in our analysis; namely work atmosphere, job security, career prospects and challenging tasks and high quality workplaces. Since none of these are directly observable to a job applicant, reliable signals must be used when a job decision is made.

5.4.2. Observable company characteristics as potential signals

According to our reversed signaling model, an observable company characteristic may become a valid signal if it is closely related to the preferred workplace characteristics and if the net returns of acquiring the characteristic are substantially lower for employers with high quality jobs than for employers with low quality jobs (otherwise an observable company characteristic could also be just a marketing trick). Since it is impossible for us as researchers, as it is for job applicants, to obtain precise information on net costs, we have to rely on qualitative reasoning to identify potential signals (for a list of potential signals see Table 5.1).[71] Empirical results will tell whether the characteristics we identified here are indeed used as signals in the labor market for skilled blue-collar workers because then employers with these characteristics would have a competitive advantage on the labor market and should therefore have lower job vacancy rates than employers without these signals (all else equal).

Table 5.1: Potential signals for skilled blue-collar workers

Potential signals (observable characteristics)	*Non-observable but highly valued characteristics*
- Apprenticeship training - Systematic continuing vocational training programs	Career prospects
- Works council	Job security
- Works council - Regular shop-floor meetings	Work atmosphere
- Overall skill level of workforce (approximated by percentage of skilled blue-collar workers) - Recruitment of workers with non-matching qualifications - Apprenticeship training - Systematic continuing vocational training programs	Challenging/interesting tasks and workplaces

The first two variables we use as potential signals for skilled blue-collar workers are *existence of apprenticeship training* and *provision of a systematic continuing training program,* which we assume signal challenging jobs and career opportunities. *Apprenticeship training* is assumed to be a reliable signal for challenging jobs because returns from apprenticeship training are certainly higher for firms using these skills later on, therefore the existence of apprenticeship training signals skill-demanding or challenging jobs for skilled blue-collar workers. Additionally, since an investment in training only pays off if the amortization period is sufficiently long, the existence of apprenticeship training also signals good long-term and career prospects. Only firms which are confident they will be in the market for a longer time

[71] As argued in the theoretical section, it is not a precondition that an observable characteristic has no direct value to the worker in order to become a valid signal. Therefore, column 2 of Table 5.1 is theoretically not restricted to job attributes workers do not care about.

span are willing to invest extensively in training (apprenticeship training typically means three years of intensive training). And only firms knowing their jobs are sufficiently attractive to retain apprentices after graduation (e.g. due to good career prospects) are willing to invest substantially in training. Therefore, having an apprenticeship program can be used as a valid signal for jobs with good long-term prospects and with sufficient career prospects. Similarly, the existence of a *systematic continuing training program* can be used as a signal for challenging jobs and good long-term prospects.

Secondly, we use the existence of a *works council* as a signal for job security and a good work atmosphere for skilled blue-collar workers. Why can works councils be seen as a signal? Because not all firms have works council despite the fact that, according to German Co-determination Law, all workers in firms above a certain size have the *right* to establish a works council. A large proportion of companies still do not have a works council. One of the reasons may be that companies implicitly or explicitly discourage workers from exerting their rights. They may just not be helpful in setting up the election procedures, they may hamper preparatory meetings or other activities, or in the worst case may even try to threaten workers to avoid works councils. As a result only 16% of all companies covered by co-determination law actually have a works council.[72] Thus the existence of a works council is not naturally given and can therefore act as a potential signal to job applicants. We argue that for skilled blue-collar workers a works council can act as a signal for job security and a good working atmosphere because works councils are generally thought to aim at securing jobs and ensure a good work atmosphere for their main clientele: typically, skilled blue-collar workers. Why are works councils a *reliable* signal and why can job applicants not just directly observe work atmosphere? Job applicants coming from the external labor market only get a quick glimpse of the company, which only gives them a highly random and incomplete picture of work atmosphere. On the other hand, the company can be assumed to report on work atmosphere with a positive bias (knowing that the applicant will have substantial difficulty in verifying such information), and just asking several incumbent employees does not provide reliable information either (because for obvious reasons incumbent workers may not be willing to make negative statements about their work atmosphere to an outsider). However, a job applicant can easily and reliably find out about the existence of a works council. Regarding the second condition for valid signals it seems reasonable to assume that the costs of having to deal with a works council are lower in companies with a better work atmosphere than in

[72] According to German Co-determination Law workers in firms with more than 5 employees (with slightly changing thresholds over the years) have the right to establish a works council, but a large number of companies do not have a works council (cf. Addison et al. 2002).

companies with a poor work atmosphere (due to insecure and unattractive jobs) because for the latter the potential for conflict is much stronger and more frequent and therefore more costly. In turn companies with poor work atmosphere have an interest in discouraging the establishment of a works council. Thus, the existence of a works council does not pay as a mere marketing trick and can therefore serve as a reliable indicator of a good work atmosphere and high job security for skilled blue-collar workers.

An alternative although less strong signal may be other forms of worker participation such as *regular, institutionalized shop-floor meetings*, which similarly to works councils can be assumed to signal a good work atmosphere. Although shop-floor meetings may from an employer's point of view primarily be used to encourage information sharing and enhance the efficiency of employees, they may still act as a signal for a good work atmosphere because it can be assumed that such meetings are only effective if a company has an open communication culture with mutual trust, which first and foremost requires a good work atmosphere. Regular shop floor meetings also do not pay as a marketing trick since the costs of having regular meetings and frequent discussions with shop-floor workers are too high if working conditions and work atmosphere are very poor. Moreover, returns are higher because shop-floor meetings only have a positive outcome if workers are willing to participate cooperatively and in a productive manner, which is more likely under better working conditions and a good work atmosphere. In addition, shop-floor meetings may directly contribute to a good work atmosphere which reinforces the effects. We assume applicants can accurately find out about institutionalized shop floor meetings just by asking randomly selected workers, since talking about having meetings can hardly be regarded as confidential information.

Thirdly, we use the skill structure of a firm's workforce (measured by the *percentage of skilled blue-collar workers*) as a signal for challenging and interesting jobs. We argue that the skill structure of incumbent workers reliably signals the quality of the jobs. Why is this? It can be assumed that *incumbent* skilled workers, who in principle value the same attributes as skilled *applicants*, would not stay with a firm if it only offered monotonous, boring jobs. Thus, firms with more challenging jobs not only need more skilled workers but are also able (and willing) to retain a higher share of skilled workers than firms with less challenging jobs. It would not pay the latter to fill their jobs with highly skilled workers, who are too expensive if a company's jobs only involve simple, monotonous activities. Therefore, if a large proportion of incumbent workers are highly skilled, this can be used as a signal for

challenging jobs.[73] Accordingly our hypothesis is: the higher the percentage of skilled blue-collar workers, the lower the job vacancy rate for skilled blue-collar workers (although it might appear to be counterintuitive).

Another proxy for challenging jobs and high quality workplaces is whether and to what extent a firm hires workers with a *non-matching occupational background* to fill a job vacancy (e.g. a job opening intended for a mechanical engineer is filled by an electrical engineer). This indicates that jobs cannot really be professionally challenging and/or that quality standards are rather poor. Thus, if vacancies are more frequently filled with workers with non-matching occupational qualifications this can be interpreted as a signal for professionally less challenging jobs. (Here, again, we do not assume that applicants know the exact proportion of jobs with non-matching qualifications, as we do in our data set, but have, rather, a more qualitative picture).

All these signals should help to explain inter-firm differences in job vacancy rates because they render a company more attractive on the external labor market and can therefore be expected to improve recruitment success: more employees are willing to accept a job offer from such a company and the job vacancy rate therefore declines. Since it seems plausible to assume that better *quality* workers (given a formal skill level) care more about signals for challenging tasks, one may additionally expect that the fraction of high quality workers should be larger in companies with good signals. Although it would be interesting to study such an impact of signaling on the *quality* of workers, our data are not sufficient to do so. Future research should try to tackle this problem, but it would need detailed information on individual productivity.

5.5. The impact of potential signals on job vacancy rates: empirical analysis

In the next section we test whether the signals listed in Table 5.1 help to explain inter-firm differences in recruitment success measured by a comparatively low job vacancy rate.

5.5.1. Estimation methods

To test the impact of our signals on job vacancy rates we estimate the following basic model:

[73] We use the percentage of skilled blue-collar workers as a proxy for the more qualitative information a job applicant may gather; i.e. we do not assume that job applicants really have the exact percentages, we only assume that they obtain a qualitative but nevertheless reliable impression of skill structure by just talking to people.

$$\begin{aligned} \text{VACANCYRATE} = {} & \beta_0 + \beta_1 \text{APPRENTICESHIP} + \beta_2 \text{CONVOCTRAINING} + \beta_3 \text{WORKSCOUNCIL} \\ & + \beta_4 \text{REGULARMEETINGS} + \beta_5 \text{SKILLEDWORKERS} + \beta_6 \text{NONMATCHQUALS} \\ & + \delta \cdot X + u \end{aligned} \tag{5.1}$$

VACANCYRATE is the *number of vacant jobs* for skilled blue-collar workers divided by the total *number of job openings* for skilled blue-collar workers (i.e. the sum of vacant and filled jobs). Thus, the dependent variable can take on values between 0, i.e. a firm was totally successful in recruiting workers, and 1, i.e. a firm was totally unsuccessful and none of the job openings for blue-collar workers could be filled. Since we focus on external recruiting, our variable *job openings* does not include internal job openings, i.e. jobs which were filled from within the company. Further, since the dependent variable *VACANCYRATE* has no negative values[74] but a considerable fraction of zero value because many firms have zero vacancies, ordinary least square estimations are not appropriate. In accordance with Wooldridge (2003: 565-73) we use a Tobit model to account for this.

As explanatory variables we use our signaling variables as given in Table 5.1: existence of apprenticeship training (*APPRENTICESHIP*), continuing vocational training (*CONVOCTRAINING*), works council (*WORKSCOUNCIL*) and regular or institutionalized shop-floor meetings (*REGULARMEETINGS*), percentage of skilled blue-collar workers (*SKILLEDWORKERS*), and recruitment of workers with non-matching qualifications *(NON-MATCHQUALS)*.

In addition, a broad set of control variables is added, including company size, location, industry, various HRM measures (incl. fringe benefits) and some variables characterizing the reputation of the product or the firm. Last but not least, the overall number of job openings is controlled for because a larger number of job openings may, on the one hand, make it more difficult to fill all openings and thereby increase job vacancy rates, but on the other hand, allow a firm to recruit more efficiently and thereby reduce job vacancy rates. Recruitment may be more efficient because with a larger number of job openings companies can afford to hire recruiting specialists or because a larger number of job openings indicates higher growth rates and thereby makes a company more attractive for potential employees. Thus, empirically, job openings could be positively or negatively correlated with vacancy rates, but in either case this has to be controlled for.

Additionally, we have to take care of a further methodological problem because job openings may not be an exogenous variable but an endogenous one, i.e. unobserved firm characteristics have an impact on the number of job openings and may also have an impact on the job vacancy rate. For example, well managed firms may be able to avoid job openings because their HR department is well organized and anticipatory, and for the same reasons well

[74] Although some firms might even have an oversupply of job applicants, it would still not bring vacancies below zero but only down to zero.

managed firms may be able to avoid job vacancies. To avoid endogeneity problems the variable job openings can be instrumented. We use the variable *labor office grants* as an instrumental variable because it can be assumed to be highly correlated with *job openings* but not with reducing job vacancies for *skilled blue-collar* workers. We can assume this because the aim of these grants is to encourage companies with job openings to hire unemployed unskilled workers. Thus, the variable is clearly related to *job openings*. However, it is not directly related to the *job vacancy rate for skilled blue-collar workers*, because the labor office grants are linked to the employment of *un*skilled workers who are widely available on the external labor market (unlike skilled blue-collar workers who were generally scarce in the period observed). Thus, we can use *labor office grants* as an instrumental variable and take the following steps to solve potential endogeneity problems: first, we estimate the impact of the independent variables plus an instrumental variable on the number of job openings; second, we estimate job vacancy rates by using the *estimated job openings* from the first step in our regression equation.

5.5.2. Data

We use a dataset based on 740 companies collected in 1999[75] with a special focus on skilled workers and competitiveness of firms, commissioned by the Institute for Small and Medium Sized Enterprises, Bonn.[76] It contains a large number of variables well suited to testing our hypotheses. Firms were asked to report the number of vacant jobs and the number of job openings they filled from the external labor market. We use these two numbers to construct our dependent variable *job vacancy rate,* which is the number of vacant jobs for skilled blue-collar workers divided by the number of vacant plus externally filled jobs for skilled blue-collar workers. We also have a large number of variables on labor relations, workplace and company characteristics.[77] The reason for using this particular data set instead of other larger surveys for Germany is that none of the larger surveys provides sufficiently detailed information for our signaling analysis. For example, we need information on job vacancy rates broken down by type of worker, on recruitment of workers with non-matching

[75] The year 1999 stands for a typical time period of prosperity, characterized by severe labor shortages in Germany (cf. Backes-Gellner et al. 2000). After the recession at the beginning of the 21st century, labor shortage became a less severe problem. However, recent developments indicate that it might already be becoming a severe problem again (Kettner 2007). Results are generalizable to other countries/labor markets or other time periods with severe labor shortages, because in all these situations companies may gain a competitive advantage over other firms by employer signaling.

[76] We thank the Institute for Small and Medium Sized Enterprises, Bonn, and particularly Rosemary Kay and Peter Kranzusch, who collected the data set and allowed us to re-use their data in our project.

[77] See Backes-Gellner et al. (2000) for the questionnaire.

qualifications for skilled blue-collar jobs, and on informal meetings, which is not available in other company data sets such as e.g. the well-known IAB-establishment panel.

Since we are interested in studying differences in *job vacancy rates* of *skilled blue-collar* workers we first exclude all companies without any job openings and second without any skilled blue-collar workers; this reduces our sample to 306 companies.[78] After eliminating observations with missing data in our explanatory variables, a sample of 204 firms was left for our analysis.[79] On average, 7.2% of job openings for skilled blue-collar workers remained vacant at the end of the year, with a standard deviation of 19.6%, indicating that there are indeed large inter-firm differences in job vacancy rates. Descriptives for all explanatory variables are given in Table 5.2. As can be seen, two of our signaling variables, *regular shop-floor meetings* and *continuing vocational training*, vary hardly at all (almost every company claims to have them), so the variables we were able to measure may not be precise and discriminating enough to function as a valuable signal.

[78] Since our theoretical and therefore our empirical analysis focuses on *skilled blue-collar* workers and on firms with job openings, the large reduction in sample size is only a minor problem. Results are anyway only generalizable to firms with skilled blue-workers and to firms with job openings. However, a comparison of the statistical means for the full sample and the reduced sample shows hardly any differences.

[79] According to Green (1991: 503) a sample of 204 observations is enough to identify medium size effects for a set of 26 variables. Moreover, there are practically no significant differences between the full and reduced sample.

Table 5.2: Definitions and descriptives of variables

Variable	Definition	Mean (Std.Dev.)
Job vacancy rate for skilled blue-collar workers	Number of vacant jobs divided by job openings (sum of vacant and filled jobs for skilled blue-collar workers), in %	0.072 (0.196)
Potential signals		
Apprenticeship	1 if there are apprentices in the company, 0 otherwise	0.725 (0.447)
Continuing vocational training	1 if workers have the opportunity to take part in continuing vocational training, 0 otherwise	0.985 (0.121)
Works council	1 if a works council exists, 0 otherwise	0.485 (0.501)
Shop-floor meetings	1 if regular shop-floor meetings are held, 0 otherwise	0.868 (0.340)
Percentage of Skilled worker share	Number of skilled blue-collar workers divided by the total number of workers	40.968 (23.912)
Non-matching qualification workers	Frequency of recruitment of non-matching workers, often = 5 to never = 1	2.721 (1.367)
Control variables		
Personnel policy		
Participation in decisions	1 if workers informally participate in important company decisions, 0 otherwise	0.515 (0.501)
Flexibility of working time	1 = high flexibility to 4 = fixed working time	2.059 (1.297)
Compensated overtime	1 if overtime is paid or compensated by additional vacation days, 0 otherwise	0.775 (0.419)
Uncompensated overtime	1 if overtime is unpaid, 0 otherwise	0.088 (0.284)
Wage above regional level	1 if wage is above regional level, 0 otherwise	0.461 (0.500)
Advertising	1 if help-wanted ads in regional newspapers, in professional journals or on the internet, 0 otherwise	0.779 (0.416)
Visibility in the labor market	1 if industry leader in visibility in the labor market, 0 otherwise	0.147 (0.355)
Monetary fringe benefits	1 if company pension, bonuses, stock ownership plans or loans are offered, 0 otherwise	0.824 (0.382)
Non-monetary fringe benefits	1 if additional vacation days, company cars or other non-monetary fringe benefits are offered, 0 otherwise	0.441 (0.498)
Product & firm reputation		
Product development	1 if market leadership in product development, 0 otherwise	3.598 (0.902)
New technologies	1 if market leadership in using new technologies, 0 otherwise	3.657 (0.957)
Closeness of customer relations	1 if market leadership in closeness of customer relations, 0 otherwise	4.059 (0.699)
Fluctuation (quota)	Number of workers who left the company in 1998 divided by total number of workers	9.894 (14.612)
Company characteristics		
Number of employees	Number of employees (log.)	4.166 (1.625)
West/East	1 if company is located in West Germany, 0 if East Germany	0.569 (0.496)
Manufacturing	1 if company is in manufacturing industry, 0 otherwise	0.564 (0.497)
Construction	1 if company is in construction industry, 0 otherwise; Reference	0.123 (0.329)
Trade	1 if company is in trade, 0 otherwise	0.123 (0.329)
Professional activities	1 if company is in professional activities industry, 0 otherwise	0.064 (0.245)
Other services	1 if company is in other services industry, 0 otherwise	0.123 (0.329)
Job openings	Number of hirings and vacant jobs divided by the total number of jobs , in %	16.766 (19.686)

5.5.3. Estimation results

Table 5.3 provides our regression results; the first column (specification 1) shows results for an estimation without accounting for potential endogeneity, in the second column (specification 2) the explanatory variable *job openings* is instrumented to account for endogeneity problems.[80] However, as can be seen by comparing specification 1 and specification 2, the results of both estimation methods are similar for all *signaling variables*.[81]

[80] A specification test (Hausman 1978) shows that an instrumental variable estimation is necessary, because the difference between ordinary least squares estimators and instrumental variable estimators is significant, indicating that the variable *job openings* is endogenous.

[81] There are some differences between specification (1) and (2) among the control variables. The variable *JOB OPENINGS* does not have a significant effect in column (1) but has a significantly negative coefficient if endogeneity is controlled for in specification (2). Thus companies with larger numbers of job openings have lower job vacancy rates. They are obviously better able to fill their job openings because their recruiting is more professional and/or they are more attractive employers with higher job growth.

Table 5.3: Tobit estimation of the job vacancy rate for skilled blue-collar workers

Variable	*Specification (1)*		*Specification (2)*	
	Coef.	Std.Error	Coef.	Std.Error
Potential signals				
Apprenticeship	-0.229**	(0.105)	-0.498***	(0.147)
Continuing vocational training	-0.284	(0.392)	-0.341	(0.384)
Works council	-0.197*	(0.111)	-0.379***	(0.133)
Shop-floor meetings	0.030	(0.120)	0.077	(0.118)
Skilled worker share	-0.005**	(0.002)	-0.003*	(0.002)
Non-matching qualification workers	0.040*	(0.024)	0.113***	(0.036)
Control variables				
Personnel policy				
Participation in decisions	-0.064	(0.066)	-0.017	(0.062)
Flexibility of working time system	0.033	(0.027)	0.051*	(0.027)
Compensated overtime	0.086	(0.094)	0.216**	(0.106)
Uncompensated overtime	0.191	(0.121)	0.467***	(0.143)
Wage above regional level	0.008	(0.065)	-0.126*	(0.074)
Advertising	0.209*	(0.107)	0.376***	(0.134)
Visibility in the labor market	-0.296**	(0.129)	-0.394***	(0.133)
Monetary fringe benefits	-0.095	(0.103)	-0.187*	(0.102)
Non-monetary fringe benefits	0.043	(0.076)	-0.086	(0.088)
Product & firm reputation				
Product development	-0.064	(0.050)	-0.033	(0.048)
New technologies	0.031	(0.040)	0.024	(0.037)
Closeness of customer relations	0.025	(0.049)	0.107**	(0.052)
Fluctuation (quota)	0.006**	(0.003)	0.022***	(0.006)
Company characteristics				
Number of employees	-0.014	(0.030)	-0.053	(0.033)
West/East	0.133*	(0.073)	0.022	(0.075)
Manufacturing	0.032	(0.113)	0.284**	(0.139)
Trade	-0.207	(0.134)	-0.008	(0.142)
Professional services	-0.472*	(0.268)	-0.753***	(0.255)
Other services	-0.165	(0.147)	0.214	(0.184)
Job openings	0.001	(0.002)	-0.033***	(0.011)
Constant	0.172	(0.471)	0.041	(0.457)
Prob > χ^2	0.007		0.002	
McFadden-R^2	0.294		0.329	
N	204		204	

Notes: Specification (1) is a simple Tobit estimation of equation (5.1); in specification (2) the variable job openings is instrumented. Robust std.errors in parentheses. *Statistically significant at the 0.10 level; **at the 0.05 level; ***at the 0.01 level. For more information about McFadden-R^2 cf. McFadden (1974).

As expected we find that firms offering *apprenticeship training* have lower job vacancy rates, meaning they were more successful in recruiting from the external labor market than firms without apprenticeship training. Since skilled blue-collar workers by definition have already completed their apprenticeship this is very strong evidence in favor of the *signaling* explanation we propose. Skilled workers have no direct benefit if a company offers apprenticeship training, however, they can use it as a signal for a high quality workplace, for

good long-term prospects and favorable career options. Apprenticeship training signals that a firm is an attractive employer for skilled blue-collar workers, which gives these firms a competitive advantage in recruiting skilled blue-collar workers and reducing labor shortages. However, our empirical results also show that the existence of *continuing vocational training* as measured in our questionnaire does not significantly reduce job vacancies (although the coefficient points in the expected direction). But the absence of significance may be explained by problems of the variable, which hardly differentiates between firms and also does not cover different types of training (which may be important for a signal).

As expected, the existence of a *works council* reduces the vacancy rate significantly. Companies with works councils enjoy lower job vacancy rates than companies without them. Job applicants use the existence of a works council as a signal for job security or for attractive workplaces with good career prospects and are more willing to accept job offers from companies with a works council. Thus works councils also provide firms with a competitive advantage on the labor market for skilled blue-collar workers. Even if job applicants may also expect a direct benefit due to the existence of a works council (for example, if they themselves are interested in becoming a works council member), for most applicants it is probably the signaling value that matters most, because not all job applicants can seriously expect to become a works council member or earn a direct private return. Thus, it is more the overall workplace attractiveness that is signaled by the existence of a works council, which makes job applicants more likely to accept jobs and gives firms a competitive advantage on tight labor markets for skilled blue-collar workers. However, *regular shop-floor meetings* as measured in our questionnaire do not have a significant effect on job vacancy rates. The absence of significance may again be explained by statistical problems of this variable: it hardly varies and there may be too many different types of meetings which we cannot distinguish but may be important in order to identify a clear signal.[82]

As expected, the *share of skilled blue-collar workers* significantly reduces the job vacancy rate and also, as expected, *employment of workers with non-matching qualifications* significantly increases job vacancy rates. Skilled workers are obviously interested in firms with a highly skilled workforce because it signals high quality standards and challenging jobs, but they are not interested in working in firms where jobs are often filled by workers with

[82] For example, in academia, where administrative meetings would have to be distinguished from research seminar meetings, having more of the former would be a negative signal whereas having more of the latter would be a positive signal in recruiting high quality faculty members. A similar distinction may be important for skilled blue-collar workers, but since we cannot distinguish different types of meetings with our questionnaire our variable REGULARMEETINGS may not represent the real signal and thus make it impossible to capture a significant signaling effect.

non-matching qualifications because this signals professionally non-challenging jobs and/or low quality standards.

The results for the control variables contain no surprises, and therefore we will not further elaborate here, but just point out two theoretically and economically important results. We find that *high wage levels* significantly reduce job vacancies, as would be expected by any economic theory. And we find that the existence of *monetary fringe benefits* significantly reduces job vacancy rates. For companies paying *wages above regional level* it is obviously easier to recruit from the external labor market to reduce skill shortages [83], and for companies providing *monetary fringe benefits* it is easier to recruit skilled blue-collar workers. Thus, as already argued by Dey/Flinn (2005), the attractiveness of a workplace is not fully determined by the level of wages; instead workers attach additional value to particular fringe benefits like company-provided health insurance in the Dey and Flinn study or other *monetary fringe benefits* in our study. [84] However, we also find that money is not all that matters because our signaling variables have a considerable impact on reducing job vacancies; the effect is at least as important as paying above average wages or offering monetary fringe benefits.

5.6. Conclusions

This chapter demonstrates how some firms are able to gain a competitive advantage on the labor market despite an aggregate shortage in skilled workers and thereby helps to explain inter-firm differences in job vacancy rates. Our study is the first to theoretically and empirically analyze the role of employer signaling in attracting skilled workers. Previous psychological or human resources studies on workers' preferences have indicated that soft characteristics of a job or workplace are important in a skilled worker's job choice. However, no previous research has shown how these typically *non*-observable soft characteristics are credibly communicated. We suggest a novel theoretical approach and reverse Spence's original signaling model to explain how employer signaling may help a firm to improve recruitment success and thereby gain a competitive advantage on tight labor markets. We determine what conditions a company characteristic has to fulfill to become a valid signal and

[83] Unfortunately, we do not have absolute wage levels in our data set. But we assume that the *relative* wage level is even more important for workers deciding on whether to accept a job or not. Moreover, omitting the absolute wage level only makes the test tougher. If there is a relationship between the absolute wage level and the potential signals it is most likely positive: firms paying higher wages are less impelled to invest in signals to attract potential employees. Thus, omitting absolute wages causes results to be downward biased and with a lower probability for significant results.

[84] Company-provided health insurance is a minor issue on the German labor market because all workers are covered by mandatory health insurance and by law all firms have to pay half of the insurance premium.

use a company data set to test our implications. Our empirical results show that some company characteristics exert a significant effect which cannot be explained by conventional theoretical arguments otherwise. For example the *existence of apprenticeship training* improves the recruitment success of skilled blue-collar workers, although skilled workers have already finished their apprenticeship and are therefore not interested in apprenticeship training per se. So companies offering apprenticeship training not only reduce labor shortages by upgrading skills within their own workforce (which is obvious and has often been studied before), but also by improving their recruitment success among skilled workers from the external labor market.

Our study is innovative in the sense that the findings go beyond what has been published about company characteristics and their impact on reducing labor shortages among individual firms. For example, although works councils have often been analyzed with respect to productivity effects or the well-being of *incumbent* workers, their value to *potential* employees and their *in*direct effects via improved recruitment success have not been studied. Likewise, apprenticeship training has been studied extensively with respect to earnings or productivity, but its *in*direct effect on avoiding job vacancies via improved recruitment success has not been studied. Only the use of the employer signaling approach pointed at studying the double effect of training on reducing job vacancy rates: internal upgrading of skills and improved external skill acquisition. To conclude, the advantage of our employer signaling model is that it helps to identify variables which would otherwise not be considered important or which would sometimes even be regarded as having the opposite effect on job vacancies. The existence of apprenticeship training does not at first glance seem to be important in the recruitment of skilled workers. However, with our employer signaling model it is clear why apprenticeships could still be important. Interestingly, such non-observable characteristics and their corresponding signals appear to be at least as important as wages.

An important and far-reaching consequence for labor relations and human resources management issues is that workplace or company characteristics should be evaluated not only in terms of their original goals and direct effects, i.e. by the returns they generate within their own policy field, but also by their signaling value or indirect effects in other policy areas. For example, the existence of apprenticeship training should be evaluated not only by the productivity effects of each individual apprentice, but also by its effect on improved recruitment. Alternatively, works councils should be evaluated not only by their direct effect, i.e. the participation and co-determination of *incumbent* workers, but also by their additional signaling effect on the external labor market, i.e. their value for *potential* employees. Our

results show that given an aggregate labor market shortage for skilled workers, individual companies can significantly improve their relative position and ensure above average hiring rates by sending high quality signals to potential employees.

CHAPTER 6

Final Remarks

The aim of this dissertation has been to study the benefits and costs of vocational education and training, considering both individuals' and firms' perspectives. Traditional cost-benefit analyses have shown that, first, the accumulation of human capital pays, and that, second, learning begets learning (for an overview, see Card (1999) and Psacharopoulos/Patrinos (2004) for education and Bassanini et al. (2005) for training). Hence, one might simply conclude that those who do not enroll in training are either irrational, or if they are rational, have an unfavorable cost-benefit ratio, which might get even worse after not having participated. This, however, has rarely been empirically investigated and, as our results demonstrate, is not to be answered by a simple yes or no. Going a step beyond traditional cost-benefit analyses, this dissertation yielded some important new insights into (non-)participation patterns:

First, we show that each educational or further training step is part of a complete educational path and training strategy and should therefore not be analyzed in isolation. On the one hand, our findings show that, even on the same level, additional education of all types – be it vocational or academic – leads to higher earnings. This is consistent with the predictions of human capital theory, but has rarely been taken into account in empirical analyses since they only look at the highest educational level. However, it is not simply the highest educational degree that matters for labor market outcomes; nor is there one combination of education that outperforms all other educational paths. Rather, various types of educational paths differ in terms of rates of return and risks. For instance, we find that educational paths with an academic entry and a vocational exit are a more profitable choice than straight educational paths. But these mixed educational paths are also associated with a (substantially) higher income risk than straight educational paths, which makes them especially attractive for risk seeking individuals. On the other hand, our results clearly demonstrate that training history matters. This not only holds for formal education but also for further or continuing training. Hence, just as one should consider each educational step (instead of focusing on the highest

educational degree), one should take account of previous training events, which then shows that even non-participants in training are not a homogeneous group. This has been neglected in the literature to date. However, the distinction between temporary (non-)participants and never-participants seems important in solving the puzzle of non-participation. While we found evidence for never-participants holding an unfavorable cost-benefit ratio (which is the conclusion one might draw from the existing evidence concerning training participation), it was less clear for temporary (non-)participants whether their cost-benefit ratio systematically differed from workers who did participate in training.

Second, though wages for the worker and productivity for the firm are certainly important outcome measures, one cannot abstract these from other types of benefits, in particular from so-called indirect benefits. Regarding workers, we show that, in the long run, even never-participants may benefit from training due to improved labor market prospects. Thus, a traditional cost-benefit comparison might miss the fact that there are also returns for those refraining from training, but that non-participation might be caused by other factors like information asymmetry (maybe these workers are not aware of the long-term benefits) or by present-orientedness (i.e., these individuals are not willing to invest without receiving an immediate gain). Regarding firms, we also provide evidence that there are additional returns (beyond productivity effects). Our findings show that for firms providing training is associated with a reduced job vacancy rate. Hence, with the choice to invest in training, companies also increase their chances of recruiting external skilled workers. These findings reveal an important and far-reaching consequence for labor relations and human resources management issues: workplace and company characteristics should be evaluated not only in terms of their original goals and direct effects, but also in terms of their signaling value or indirect effects in other policy areas.

Third, in addition to the obvious monetary cost component, there are also non-monetary costs (i.e., the time spent in training) attached to training participation, which should be considered separately. Our findings indicate that firms generally support their workers by bearing (part of) the monetary *and* non-monetary training costs. However, for workers, non-monetary costs seem to form the main binding restriction. Thus, assessing the various cost components helps to understand non-participation.

To summarize, aside from various benefit and cost measures, risk preferences, information asymmetry, and time preferences have all been identified as crucial factors that explain workers' educational and training decisions. Although various factors might prevent workers

from participating, it is important to point out that most workers should basically benefit from training, at least in the long run. This is important, insofar as rapid technological change and demographic trends might further increase the demand for highly skilled workers.

Turning to the firm-based perspective, the prevalence of employer-supported training underscores the importance of firms' having a skilled workforce. Obviously, in order to stay competitive, firms substantially support their workers' training and do not solely rely on recruiting skilled workers from the external labor market. This is insofar important as our results demonstrate that with the provision of training companies can ensure above average hiring rates. However, it remains an open issue whether, for those firms that do not offer apprenticeship or further training opportunities, these indirect effects would also be marginal or whether these firms are not aware of such relations.

Last (but not least), the empirical findings point toward several preliminary policy implications, which should be a focus of future research. Since our results indicate that various types of educational paths (i.e., combinations of vocational and academic education) are worthwhile strategies, the permeability of a national education system becomes important. There may be some value to increasing permeability, and especially to facilitating changes between the two sectors of the educational system. This might reduce both the time lost and the risks associated with following mixed educational pathways. However, due to technological changes and demographic trends, it does not suffice to focus on formal education. Rather, lifelong learning should be encouraged. On the one hand, participation in continuing vocational training might be increased by raising workers' awareness of returns that are not directly associated with their current job, but which might lie far in the future. On the other hand, workers who are not willing to bear training costs and who lack employer support could be motivated through short-term financial incentives attached to completed training in order to overcome exceptionally high discount rates. For instance, Angrist/Lavy (2004) present evidence that financial incentives do indeed increase high school certification rates among low-achieving students. Likewise, Messer/Wolter (2009) show that adult education vouchers increase the training participation rate. However, the authors emphasize that there is also a crowding out (i.e., some of the workers who use the voucher would have been willing to self-finance training). Thus, the efficiency of such policies is not beyond dispute. Alternatively, one could also think about support in terms of non-monetary costs. For instance, institutional environments should be compatible with the provision of training during working hours. This might generally reduce training obstacles for a large number of current non-participants.

Finally, we appreciate your interest in and the time spent by reading this dissertation - now even more because we know that “time is more costly than money.”

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