Job-training of Hungarian higher-education graduates[*]

by Peter Galasi

Abstract

Considerable amounts of time and money are spent on job-training of school-leavers graduated from higher-education institutions. More than a half of the employees in our sample participated in job-training between graduation date (1999) and September 2000. The work in this paper considers two aspects of the problem. First, the relationship between training probability/training length and the initial human capital (proxied by level of education and in-school labour market experience) is concerned with, and, second, some elements of the training-cost-sharing decision is analysed. There are some signs that university education reduces the probability of training as compared to college education, whereas in-school labour market experience increases it. University education reduces training length, as well. In-school labour market experience has no effect on the length of job-training. Another important result is that school-leavers holding diplomas with “narrower” types of education are more likely to obtain training, and also to have longer training programmes. This implies a more severe matching problem in the case of “narrower” types of education, possibly due to prohibitive searching costs for finding a good-quality match. Results for the cost-sharing decision are in line with Becker’s idea, since the firm is less likely to entirely cover the costs of general training and more likely to finance job-specific training programmes.

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Introduction

Job training constitutes important part of both the labour market and the educational system. A labour-market-centred human-capital approach to the problem has become integral part of the labour economics since the mid-60's (for theoretical summaries see Becker 1962 and 1975, Hashimoto 1981, Parsons 1990, Stevens 1994).

In the '90s, training seems to be more important as ever in Hungary, especially among young higher-education gra duates. When leaving full-time education many higher-education graduates continue accumulating knowledge and skills through formal or informal, on-the-job or off-the-job training. Training might improve the productivity of young school-leavers, contribute to forming better job-employee matches, ameliorate their opportunity for obtaining stable and higher-paid jobs.

The paper focuses on two elements of the problem: first, the role education level might play in determining the probability and the length of training, and, second, the share of training costs between employer and employee will be investigated.

As regards the relationship of education level with training probability (occurrence and length, etc) it is of great importance whether education level and training are positively or negatively correlated. If the former holds then differences in human capital between employees with lower and higher levels of education will widen on the labour market, and the less educated will have lower chances for ameliorating their labour market position by training, and the more educated will be able to accumulate even more human capital. If the reverse is true then differences due to in-school human capital will be diminished on the labour market.

The literature provides no unambiguous answer to the problem. This is not surprising since actual predictions and results depend on both the theoretical contexts of the models and the properties of data (especially the time horizon the samples cover). In a simple short-run setting, where more education implies higher job-productivity, and the training is intended to provide workers with additional skills and knowledge so as to reach actual (fixed) job-productivity, more education is associated with lower training probability for a given job, and this is the case if more education indicates better learning abilities, as well. In a long-run utility- (profit-) maximisation model, where the more educated have better learning abilities thus lower marginal training costs and/or higher returns to training, workers with higher levels of education will experience more training, especially in the case of firms with long career ladders or „internal labour markets". The problem becomes more complex if jobs are allowed to be heterogeneous in their job-specific skill-requirements (the amount of job-specific knowledge needed in the job), because both kinds of model might then produce either positive or negative coefficients depending on the distribution of levels of education and learning abilities among jobs with different job-specific skill-requirements. Some models (see Belzil and Hansen 2002 for an example) distinguish between school ability (taste for school) and market ability (earnings potential), both of them affecting the discount rate used in the schooling/ labour market entry decisions, and that might have consequences on the predicted relationship between training probability (occurrence, length) and education. If, for example, individuals with higher market ability choose lower levels of schooling, and are more productive in a job, given their better skills required by the job, then in a short-run fixed-productivity-requirements setting they need less training, thus the more educated will get more training. In a long-run setting, however, the result might be the opposite; since individuals with higher market ability choose less schooling, and have better learning skills required by the job, then their marginal training costs will be lower and/or their returns to training higher, thus they will be more likely to be trained, than individuals with higher levels of education. The interpretation of empirical results is even less clear-cut, since both ability and job-specific skill-requirements are normally unobserved.

The papers of Lillard and Tan (1992), Lynch (1992), van Smoorenburg and van der Velden (2000), Goux and Maurin (2000), Ariga and Brunello (2002), Garcia, Arkes and Trost (2002) assume/obtain either negative, or positive correlation, or both, and the values of the estimated coefficients also show a great variety of patterns. van Smoorenburg and van der Velden (2000), focusing on the training probability of Dutch career-beginners, argue that higher level of education implies higher ability and this reduces the costs of a given training, therefore level of education and training probability will be positively correlated. The estimated parameters support their hypothesis, and the result is robust to model specifications. Almost the same holds for Lillard and Tan's paper, since in their empirical model, especially for the sample of young men, company training and educational level are positively correlated up to 16 years of schooling, but then for individuals with 17 and more years of schooling the value of the coefficient decreases, that is, the most educated less probably participate in training that those with 16 years of schooling. In Ariga and Brunello's paper more education might lead to more training since education improve learning skills therefore reduces marginal training costs but it might also be that the more educated get less training because they have higher marginal costs either because they have lower learning skills in jobs requiring training, or higher opportunity costs of training, or both. Their estimates result in a negative relationship between education and training in the case of on-the-job training. Goux and Maurin (2000) find that training is the least prevalent among the less educated but no significant parameter estimate is produced otherwise. Garcia, Arkes and Trost's (2002) results show that, with using high school as the reference, both lower and higher levels of education leads to lower training-participation probability. Lynch's off-the-job-training participation probit produces positive and significant parameters for both high-school and post-high-school education (lower-than-high-school education being the reference), but the value of the post-high-school parameter is less than that of high-school one. Moreover her other estimations produce mainly non significant coefficients. The empirical results are then mixed due to different model specifications, and also different samples.

The second problem is how the employer and the worker share the costs of training. In the spirit of Becker's (1962) fundamental model, training might be classified as perfectly general and specific. Training is (perfectly) general if worker's productivity (marginal product) increases by the same amount with many employers. It is (completely) specific if the increase of productivity with a given employer does not affect productivity with other employers. Since both parties can terminate the contract in the future, sharing the costs serves as an element of insurance against future losses in returns. One implication of the model is that general (specific) training is financed by the worker (the employer), and in-between (neither completely specific, nor perfectly general) training implies cost sharing between the parties. Other elements of the problem might be also of interest: how level of education of the worker affects the cost sharing decision, that is, whether the firm is more likely to finance the training for less or more educated workers, how the proportion of costs covered by the firm or the worker is related to the total cost of training, and, finally, how cost sharing between the two parties changes in response to increases/decreases in (expected) post-training wages.

In this paper we make use of a sample of Hungarian full-time higher-education school leavers, graduated in 1999 whose September 2000 labour market position has been observed. Only formal training of the actually employed is considered, thus learning by doing is excluded from the analysis, and the data do not allow us to distinguish between off- and on-the-job training.

Data, estimation strategy and empirical specification

The sample include young workers with higher education diploma, some 53 per cent of them took part in training and, on average, spent 61 days on training between graduation (summer of 1999) and September 2000. The sample is representative of full-time students of the Hungarian higher education who finished their studies in 1999 and were employed in September 2000. Since the structure of the sample is not the same as that of the whole population in terms of the number of graduates by higher-education institutions and types of education, here weighted data are used.[1]

Three equations will be estimated: a training-participation-probability, a training-length, and a cost-sharing equation.

Let us see first the training-probability equation. A key explanatory variable – as we have seen in the literature – is human capital. In the spirit of the standard, Mincerian human capital model (Mincer 1974), it has two components: one accumulated by attending school and one on the labour market (labour market experience).

[1] The weights were constructed on the basis of institution- and type-of-education-level higher-education statistics collected by the ministry of education.

In our case both components are initial, pre-labour market and pre-training human capital endowments. We know the highest educational degree of the respondents, and we use this as a proxy for human capital accumulated by attending school. Since our workers are all higher-education graduates, this results in a dummy variable: college (or bachelor) degree (with 2-4 years of higher education, = 0) and university (or master) degree (with 5 to 7 years of higher education, = 1). The proportion of university diploma-holders is 39 per cent.[2] For the other component (labour market experience) we use in-school labour market experience. This is measured by a dummy: whether the respondent regularly worked for pay during his/her study (no = 0, yes = 1), and almost one third of the respondents possess in-school experience.[3] As regards the expected sign of the coefficient the problem is similar to that of education. In a short-run setting where training is intended to bridge the gap between initial human capital and actual productivity requirements in the job, if in-school experience leads to higher productivity at the work place, the correlation will be negative, and this would be the case if in-school experience indicates good abilities/skills required by the job. In a life-cycle model if in-school experience results in higher productivity, and/or indicates better learning skills in training, then the more experienced will be more likely to be trained. When estimating the training-probability equation, the question of sample selection arises since workers constitute a pre-selected sample of higher-education graduates. For this reason we have estimated a probit with sample selection (Maddala 1983) with a labour-market-participation and a training equation, where the selection (labour-market-participation) equation contains the average level of unemployment of types of education that is not also in the training probability equation. If the error terms of the two equations are not correlated, the hypothesis of sample selection is rejected, and the training participation probability equation will be reestimated by simple probit.

In addition to variables proxying human capital endowments, two other variables have been inserted in the model in order to capture the effect of workers' heterogeneity on training probability. A series of dummies has been included so as to detect how types of education might affect training probability (reference category: teachers in primary schools). These variables might reflect differences in labour demand for skill s embodied in types of education. A type of education represents a special combination of skills learned in school, and the marketability of a given combination of skills depends on the actual state of the labour market. This might influence the quality of education/job match, and a better-quality match might lead to lower training probability. An occupational concentration index[4] is also inserted into

[2] For means and standard deviations of the variables, see Appendix Table A1.
[3] It seems that in-school experience might be empirically important in wage determination (see Light 2001).

[4] The index for type of education i with occupations o is as follows : $K_i^o = (1 - \sum_o p_{io}^2)\frac{N_o}{N_o - 1}$,

where p_{io} denotes the proportion of individuals with type of education i working in occupathe equation. It shows how individuals with a given type of education are distributed among occupations. Some types of education provide skills that might be useful for a relatively large number of occupations - they are labelled „broad" fields of education by van Smoorenburg and van der Velden, some prepare students for a small number of occupations („narrow" fields of study). The concentration index is used to proxy this problem. Its value is zero if individuals with a given type of education are employed in only one occupation, it is one if individuals with a given type of education are distributed evenly among occupations. A type of education with zero value is, in this sense, very „narrow", whereas a field of study with a unit value is very „broad". „Narrower" fields of study can assure education/job match of better quality but with relatively high searching costs, that is, it might be costly to find a good match due to the „narrowness" of the type of education. „Broader" fields of study might result in a match of worse quality but with relatively low costs of searching. If an individual with a „narrow" type of education can find a job with a good-quality match, he/she needs little or no training. If not, then much training will be necessary in order to bridge the gap between actual skills and job requirements. Individuals with „broader" types of education can be employed in many occupations but need some training due to the relative worse quality of the match. The sign of the estimated coefficient can be either positive or negative. Negative sign means that individuals with „broader" („narrower") types of education are less (more) likely to be trained, thus „broader" types of education produce a better education/job match than the „narrower" ones, and consequently „broader" fields of study imply less training costs. With a positive sign the reverse holds.

Finally, a series of firm-size dummies is included (firms with more than 1000 employees as reference). One can argue that firm's size affects training costs. There are some signs that larger firms train their employees to a greater extent than smaller ones (van Smoorenburg and van der Velden 2000), and this can be attributed to economies of scale larger firms might have in providing and/or purchasing training services. As for the costs of training they can be spread over a larger number of employees with larger firms and/or larger firms can purchase training courses at lower prices. One can also argue that larger firms provide more stable and better job opportunities so that it is more advantageous for workers in larger firms to participate in training. If this is so, training probability and firm size will be positively correlated.

As regards the training-length equation, the dependent variable is the natural log of the length of training measured in days. The structure of the problem is similar to that of training probability, but the question is not the same. If training length is an indicator of resources spent on training, then the relationship between human capital and the resources spent on training is considered. Here a sub-sample of employees

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tion *o*, N_o is the number of occupations, and $0 \leq K_i^o \leq 1$. If it is zero, then individuals with a given type of education are concentrated in one occupation. If it is one, individuals with a given type of education are distributed evenly among occupations (van Smoorenburg-van der Velden, 2000).

are considered, namely, those having received training. The same explanatory variables are used as in the training probability equation, for similar reasons and their interpretation is also similar.

The equation can be estimated by ols but it is very likely that the schooling variable is endogenous. This might be due to the unobserved heterogeneity of individuals in terms of productivity or/and ability needed in the job and also to the heterogeneity of jobs in terms of firm-specific skill-requirements. Levels of education and (unobserved) productivity/ability and/or firm-specific skill requirements might be correlated, and as a consequence ols would produce biased parameter estimates for the schooling variable. The empirical model will be estimated by 2sls with one IV[5], and we will check the direction of the bias by running ols, as well.

As an instrument the date (year) of admission to the higher education institution will be used. The individuals in our sample were admitted in different years and this variable must be correlated with the schooling variable, since, first, persons graduated from colleges have 2-4 years of education, whereas for those attended universities the length of study is 5 to 7 years, and, second, all of them graduated in the same year (1999). In addition, it is very unlikely that the date of admission would be correlated with the length of training. We have run two tests to check these assumptions. The instrument can be considered valid if regressing the potential endogenous variable on all the exogenous variables and the instrument and using ols, the partial effect of the instrument on the potential endogenous variable proves significant (produces a significant *t* value). As regards the endogeneity of education a regression-based Hausman test is used (Wooldridge 2002). First, education is regressed on the instrument and the exogenous variables, second, the ols residuals of this equation are included in the reduced-form equation and it is estimated by ols. If the parameter estimate of residuals is significant, the exogeneity of education can be rejected. Test results are included in tables reporting 2sls estimations, and they support both the validity of the instrument and the endogeneity of education.

The cost-sharing equation might be estimated by either ordered probit and/or probit and/or probit with sample selection. As regards the possible dependent variable for an ordered probit, three states may be distinguished: the training is financed by the worker and/or his/her family (= 1), this affects some 45 per cent of the workers, and by the worker and the firm (= 2), 9 per cent, and entirely by the firm (= 3), 46 per cent. If the estimator is the probit or the probit with sample selection, the best candidate for the independent variable is a dummy: whether the training is financed entirely by the firm (=1) or otherwise (=0). Since it is likely that (self-)selection into a training programme is not random, the coefficients of both the ordered, and the simple probit might be biased. For this reason we have estimated the model by probit with sample selection. As for the selection equation, our training probability equation

[5] Another potentially endogenous variable is the in-school experience dummy. We could not find a valid instrument for this variable. We have run several model for finding one but either

is used (see above). The model is identified since there are some variables in the selection equation that are not in the cost sharing equation.

The explanatory variables include two dummies proxying the general/specific nature of the training, the two human capital indicators (education and experience), the length of training (in days, natural log), the post-training wage (wage rate, natural log), and a series of firm-size dummies.

As regards the construction of the variable(s) for the character of the training, we know its objective/purpose (learning a foreign language; computer skills; supplementary skills needed in the actual job; special skills needed in the actual job; skills needed in another job, learning for personal interest; training prescribed by the law), that might have something to do with the genelar/specific nature of the training. Some of the objectives, however, cannot be interpreted in the specific/general frameworks (training required by the law), for some it is hard to decide whether it would be specific or general (skills needed in another job, personal interest). We have two kinds of training programmes that might be considered as general: foreign language and computer skills. Foreign language and computer skills are more or less transportable, that is, they can be utilised at many firms. Strictly speaking no information can be obtained from the data on whether the training is firm-specific or not. Rather, some training programmes seem to be job-specific, namely, special and supplementary skills needed in the actual job. Although these are not necessarily firm-specific training programmes, one can argue that the knowledge and skills accumulated with the help of these programmes are less transportable than foreign language and computer skills, thus in the spirit of the Becker's model we can expect that firms will be more likely to finance these programmes, than those providing general knowledge and skills. We have then included two dummies one for general and one for job-specific training programmes, and the reference is the dummy representing all the other programmes being assumed a mixture of not perfectly specific and not completely general programmes. If the classification works and the assumptions are correct, we expect a positive sign for the specific, and a negative one for the general dummy.

Education and in-school labour market experience might play a role in cost-sharing decisions. If more education and experience indicate better abilities, learning skills and higher productivity in the job, then, from long-run profit-maximisation considerations, it might be advantageous for the firm to cover the training costs for the better educated and more experienced to a greater extent.

Higher post-training wage implies higher post-training costs, that is, less expected profit at fixed expected post-training productivity. This might induce firms to cover smaller proportions of the training costs in order to minimise their losses for the training and post training period. If this is so, then higher post-training wages would result in smaller firm's shares. At the same time, post-training wage may reflect firm's

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the potential instrument did not prove valid, or the model specification was problematic with having produced negative R-squared statistics.

expectations as regards post-training productivity of the trainee. If the firm expects high productivity increase due to training, that is, high post-training productivity, then it would be willing to cover a greater proportion of the training costs, than in the case of lower post-training productivity and wage. Then higher post-training wage results in a more intensive participation in financing the training programme on the part of the firm. Training length is also included in the equation so as to control for differences in the amount of training workers need.

Firm-size dummies are inserted in the equation, and it is assumed that due to economies of scales, lower fixed per capita training costs, and better intra-firm job-mobility opportunities, larger firms cover the costs of training with higher probability than smaller ones.

Results

Estimation results for the training probability and length are reported in Table 1 and 2. As regards training probability (Table 1), having made use of probit with sample selection seems to be justified for the error terms of the training probability and employment probability equations are correlated. The parameter estimate for university education is negative but it is significant only at the $p = 0.1$ level, as for the coefficient of in-school experience the model has produced a positive and significant estimate. This suggests that there are some signs that the university diploma results in lower training probability than the college diploma, and that in-school experience increases the probability of training. The first result is consistent with a fixed-productivity-requirement model where training is aimed at increasing productivity level and the less educated are initially considered less productive than those with higher education. The second one can be interpreted in the framework of a long-run model: in-school experience might result in higher productivity, indicate better learning skills in training, then the more experienced will be more likely to be trained.

We have estimated the training-length equation by ols and 2sls (Table 2). The instrument-validity and the endogeneity tests have proven successful (as it can be seen at the bottom of the tables displaying estimation results), so 2sls estimations are considered as producing the „true" coefficients, but in order to check the direction of the parameter biases for the education variable it is worth comparing the ols and 2sls results.

Both ols and 2sls estimations have produced significant and negative parameters for the education variable. No significant coefficient has been obtained for the in-school experience variable. Thus in-school experience does not affect training length, and persons with university education participate in shorter training programmes, than those with college education. The difference is quite large: the average university diploma-holder spends 44 per cent less days on training than the average person with college degree. Moreover, the ols estimation is biased downward, it underestimates the effect of education on training length with a coefficient value indicating 23 per cent less days of training for university education. The negative relationship between education and training length is consistent with a short-run fixed-productivity-requirements model where training is intended to help workers with less human capital in reaching the productivity level demanded by the job. The direction of the bias can be interpreted as follows: persons with college education systematically differ from those with university education in their abilities needed in the job or/and their earnings potential (market ability). More able individuals choose lower levels of schooling (college education), then the ols underestimates the strength of the relationship for when estimating the model by ols unobserved abilities cannot be taken into account.

The estimated coefficient of the occupational concentration index is significant and negative in both the training-probability and the training-length equations and for all specifications, suggesting a more severe matching problem for persons having a „narrow" type of education. Those having obtained a diploma with „narrower" types of education have higher training probability and longer training programmes. This implies that they are more likely to enter jobs with a job/education match of worse quality than those having „broader" types of education, that might be due to higher searching costs of finding a good match.

Agricultural education results in the highest probability of training, foreign language, humanities, economics&business, technical education and informatics also produce relatively high parameter values. The high coefficient value associated with agricultural education suggests severe matching problems due to decreasing demand of the agriculture in the '90s and the parallel increase in higher-education output. As regards diplomas in humanities and foreign languages it might be that the proportion of school-leavers with unsatisfactory practical (job-related) knowledge is high. The relatively high training probability for persons with economics&business, technical education, and specialised in informatics is a kind of surprise since it might be assumed that the demand for these types of education is high and that the knowledge provided by these types of education can be used in many jobs. The result shows that high demand does not exclude high probability of training.

As for the effect types of education may have on the length of the training, diplomas in natural sciences, humanities, foreign languages and agricultural education lead to longer training. Technical education, business&economics, and informatics are all characterised with shorter periods of training. Medical education implies even less training in terms of training length, meaning that school-leavers with medical diplomas mostly enter jobs in health care.

Training probability and length putting together, agricultural education produces high probability of training and long training, and this also holds for humanities and foreign languages. Natural sciences result in low training probability and long training. Finally, technical education, informatics and business& economics are associated with relatively high training probability and short periods of training.

Firm size is positively related to training probability (most of the coefficients are significant with greater values for bigger firms), and school-leavers spend more time on training with smaller firms (50 or less employees) as compared to the biggest firms.

Results from cost-sharing equations are reported in Table 3. Panel A of the table displays the estimated model, in panel B marginal effects are shown. The assumption that the cost-sharing equation might produce biased parameter estimates in the case of a simple probit is supported by our results since the selection (training probability) equation and the cost-sharing equation are not independent, their error terms are correlated (see the Wald test at the bottom of the table).

As regards the education variable, the parameter estimate is significant and positive, that is, the firm is more likely to cover the costs of training for persons with university than those with college education. This confirms the hypothesis that more education indicate better abilities, learning skills and higher productivity, and less marginal training costs, thus the firm is more willing to finance the training of university diploma holders.

As regards in-school experience, no significant coefficient has been resulted from the estimations. The same holds true of the wage-rate variable, its parameter estimations are significant only at p=0.15 level.

The length of training is negatively correlated with the probability with which the firm will entirely cover the costs of training. It is in line with an interpretation that the profit-maximising firm ex ante sets the amount of money it is willing to spend on training, and if the actual training programme requires more time or higher costs then it reduces its share in the total training costs.

We can see that the variables for general and job-specific training have performed well. The parameters are significant and they have the expected signs: a negative one for general and a positive one for job-specific training. This implies that the results are in accordance with Becker's idea about the relationship between inter-firm transportability of skills produced by and the cost-sharing of training.

Firm-size is also positively correlated with firm's willingness to cover training costs, the parameters for all the dummies are significant and negative (biggest firms are the reference), and the value of the coefficient gets higher as firm's size increases. This is in line with hypotheses concerning economies of scales, lower fixed-costs of training, and more intensive intrafirm mobility with bigger firms.

Summary

Firms and employees spend considerable amounts of time and money on the job training of school-leavers graduated from higher-education institutions. More than a half of the employees in our sample participated in job training between graduation date (Spring-early Summer 1999) and September 2000. The average length of the training programmes were 61 days.

The work in this paper considered two aspects of the problem. First, the relationship between training probability/training length and the initial human capital (proxied by level of education and in-school labour market experience) was considered, and, second, some elements of the training-cost-sharing decision were analysed.

There are some signs that university education reduces the probability of training as compared to college education. This is consistent with a short-run fixed-productivity requirements model where training is intended to increase the productivity of the career-beginners in order to reach the level of productivity needed in the job. At the same time, in-school labour market experience increases the probability of training. This might mean that in-school experience indicates better job-abilities resulting in lower marginal costs of and/or higher marginal returns to training.

University education reduces the length of the training, as well. Thus school-leavers with university diploma have shorter training programmes than those graduated from colleges. This is also consistent with a short-run fixed-productivity-requirements approach to job-training decision, for the more educated have more initial human capital that results in higher initial productivity thus less additional human capital is needed at fixed job-productivity requirements. One important result is that the coefficient for education estimated by ols is downward-biased. This might be interpreted as follows: persons with college education have better abilities needed in the job and/or greater earnings potential (market ability) than those with university education, therefore more able individuals choose lower levels of schooling (college education). In-school labour market experience has no effect on the length of job-training.

One can conclude that there is a negative relationship between level of education and job-training costs. If the school-leaver enters the labour market with more education, then he/she needs a shorter training programme so as to reach the productivity level required by the job. Then it might be advantageous for the cost-minimising firm to hire school leavers with university rather than those with college education. If the costs of education plus training a worker needs for reaching the productivity requirements of a given job are fixed then hiring a more educated school-leaver for the job is tantamount to the redistribution of the total education and training costs to the detriment of state budget that covers most of the costs of education.

Another important result with potential policy implications for the higher-education institutions is that school-leavers holding diplomas with “narrower” types of education are more likely to obtain training, and also to have longer training programmes. This implies a more severe matching problem in the case of “narrower” types of education, possibly due to prohibitive searching costs for finding a good-quality match.

Results for the cost-sharing decision are in line with Becker's idea, since the firm is less likely to entirely cover the costs of general training and more likely to finance job-specific training programmes.

As regards the relationship between education and training costs, the firm is rather willing to cover the costs of training for the more educated (university degree) than those with college education.

Longer training programmes reduce, the size of the firm increases firm's share in training costs.

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Tables

Table 1 Determinants of training probability

A. Estimated coefficients

Variable	Coef.	Robust Std. Err.	z	P>|z|
University	-0.077	0.041	-1.90	0.058
Experience	0.214	0.039	5.50	0.000
Type of education				
Agricultural	0.544	0.162	3.37	0.001
Humanities	0.546	0.141	3.88	0.000
Foreign Language	0.479	0.149	3.21	0.001
Small Languages	0.506	0.320	1.58	0.114
Physical Education	0.585	0.224	2.61	0.009
Teaching (BA)	0.000	0.000	0.00	0.000
Informatics	0.490	0.140	3.51	0.000
Technical	0.529	0.147	3.60	0.000
Arts	0.139	0.265	0.52	0.602
Medical	0.488	0.088	5.57	0.000
Law	0.489	0.124	3.93	0.000
Business&economics	0.559	0.148	3.77	0.000
Social Sciences	0.557	0.191	2.91	0.004
Natural Sciences	0.236	0.138	1.71	0.087
Occupational concentration	-1.088	0.313	-3.47	0.001
Firm size				
10 or less	-0.333	0.063	-5.30	0.000
11 to 50	-0.236	0.054	-4.38	0.000
51 to 100	-0.240	0.059	-4.08	0.000
101 to 500	-0.101	0.054	-1.86	0.064
501 to 1000	-0.152	0.072	-2.13	0.033
1000+	0.000	0.000	0.00	0.000
Constant	0.405	0.184	2.20	0.027
Number of obs				5331.000
Censored obs				1170.000
Uncensored obs				4161.000
Wald chi2(21)				176.610
Prob > chi2				0.000

B. Marginal effects

	Coef.	Robust Std. Err.	z	P>|z|
University	-0.030	0.041	-1.90	0.058
Experience	0.084	0.039	5.50	0.000
Type of education				
Agricultural	0.215	0.162	3.37	0.001
Humanities	0.215	0.141	3.88	0.000
Foreign Language	0.189	0.149	3.21	0.001
Small Languages	0.199	0.320	1.58	0.114
Physical Education	0.230	0.224	2.61	0.009
Teaching (BA)	0.000	0.000	0.00	0.000
Informatics	0.194	0.140	3.51	0.000
Technical	0.208	0.147	3.60	0.000
Arts	0.055	0.265	0.52	0.602
Medical	0.193	0.088	5.57	0.000
Law	0.193	0.124	3.93	0.000
Business&economics	0.220	0.148	3.77	0.000
Social Sciences	0.219	0.191	2.91	0.004
Natural Sciences	0.093	0.138	1.71	0.087
Occupational concentration	-0.423	0.313	-3.47	0.001
Firm size				
10 or less	-0.129	0.063	-5.30	0.000
11 to 50	-0.092	0.054	-4.38	0.000
51 to 100	-0.093	0.059	-4.08	0.000
101 to 500	-0.039	0.054	-1.86	0.064
501 to 1000	-0.059	0.072	-2.13	0.033
1000+	0.000	0.000	0.00	0.000

Probit with sample selection
Independent variable: has the individual participated in training?

The selection equation includes: whether the individual is employed or not (dependent variable), an education, an in-school experience, 14 types of education dummies plus the average unemployment rate of types of education (explanatory variables)
Wald test of independent equations (rho = 0): chi2(1) = 39.15 Prob > chi2 = 0.0000

Table 2 Determinants of the training length

ols

Variable	Coef.	Robust Std. Err.	t	P>|t|
University	-0.257	0.101	-2.53	0.011
Experience	-0.126	0.089	-1.41	0.159
Type of education				
Agricultural	1.381	0.388	3.56	0.000
Humanities	1.562	0.343	4.55	0.000
Foreign Language	1.402	0.365	3.84	0.000
Small Languages	0.927	0.688	1.35	0.178
Physical Education	1.078	0.513	2.10	0.036
Teaching (BA)	0.000	0.000	0.00	0.000
Informatics	0.338	0.344	0.98	0.325
Technical	0.888	0.356	2.49	0.013
Arts	0.022	0.415	0.05	0.958
Medical	-0.493	0.208	-2.37	0.018
Law	1.186	0.279	4.26	0.000
Business&economics	0.728	0.360	2.02	0.043
Social Sciences	0.909	0.458	1.98	0.048
Natural Sciences	1.573	0.328	4.79	0.000
Occupational concentration	-2.580	0.747	-3.45	0.001
Firm size				
10 or less	0.508	0.146	3.48	0.001
11 to 50	0.347	0.134	2.59	0.010
51 to 100	0.001	0.147	0.00	0.997
101 to 500	0.169	0.138	1.23	0.220
501 to 1000	-0.046	0.180	-0.26	0.797
1000+	0.000	0.000	0.00	0.000
Constant	4.336	0.431	10.05	0.000
N				2063
F				7.45
Prob > F				0
R-squared				0.0676

2sls

Variable	Coef.	Robust Std. Err.	t	P>|t|
University	-0.582	0.197	-2.96	0.003
Experience	-0.096	0.092	-1.04	0.298
Type of education				
Agricultural	1.980	0.503	3.93	0.000
Humanities	2.151	0.467	4.61	0.000
Foreign Language	1.967	0.475	4.14	0.000
Small Languages	1.414	0.822	1.72	0.085
Physical Education	1.511	0.566	2.67	0.008
Teaching (BA)	0.000	0.000	0.00	0.000
Informatics	0.733	0.405	1.81	0.070
Technical	1.412	0.456	3.10	0.002
Arts	0.491	0.456	1.08	0.281
Medical	-0.379	0.218	-1.74	0.082
Law	1.607	0.357	4.50	0.000
Business&economics	1.256	0.458	2.74	0.006
Social Sciences	1.338	0.517	2.59	0.010
Natural Sciences	2.128	0.439	4.85	0.000
Occupational concentration	-3.663	0.946	-3.87	0.000
Firm size				
10 or less	0.504	0.147	3.43	0.001
11 to 50	0.334	0.135	2.48	0.013
51 to 100	0.002	0.147	0.01	0.991
101 to 500	0.190	0.139	1.37	0.172
501 to 1000	-0.033	0.183	-0.18	0.856
1000+	0.000	0.000	0.00	0.000
Constant	4.925	0.528	9.32	0.000
N				2056
F				7.31
Prob > F				0
R-squared				0.0626

Dependent variable: length of the training (natural log)
Endogenous variable: university; Instrument: date (year) of admission into the higher-education institution
Validity of instrument: t-value = -16.67
Endogeneity of education: t-value 2.04 (p=0.042)

Table 3 Determinants of cost-sharing

A. Estimation results

	Coef.	Robust Std. Err	z	P>|z|
Legth of training	-0.299	0.031	-9.60	0.000
Wage rate	0.051	0.035	1.46	0.144
Job-specific training	0.129	0.057	2.25	0.025
General training	-0.181	0.072	-2.53	0.012
University	0.207	0.061	3.37	0.001
Experience	0.021	0.057	0.37	0.710
10 or less	-0.826	0.101	-8.16	0.000
11 to 50	-0.703	0.078	-8.97	0.000
51 to 100	-0.559	0.086	-6.47	0.000
101 to 500	-0.258	0.080	-3.24	0.001
501 to 1000	-0.252	0.100	-2.51	0.012
Constant	0.079	0.241	0.33	0.741

B. Marginal effects

	dy/dx	Robust Std. Err	z	P>|z|
Legth of training	-0.080	0.010	-7.68	0.000
Wage rate	0.014	0.009	1.46	0.144
Job-specific training	0.034	0.016	2.21	0.027
General training	-0.048	0.019	-2.48	0.013
University	0.057	0.018	3.16	0.002
Experience	0.006	0.015	0.37	0.711
10 or less	-0.162	0.015	-11.13	0.000
11 to 50	-0.162	0.016	-10.17	0.000
51 to 100	-0.125	0.016	-7.90	0.000
101 to 500	-0.064	0.018	-3.53	0.000
501 to 1000	-0.061	0.022	-2.80	0.005
Number of obs	3590			
Censored obs	1975			
Uncensored obs	1615			
Wald chi2(11)	227.91			
Prob > chi2	0			

Probit with sample selection; dependent variable: the firm entirely covers the costs of training
The selection equation includes: whether the worker participated in training or not (dependent variable), an education, an experience, 14 types of education and 6 firm-size dummies plus an occupational concentration index (explanatory variables)
Wald test of independent equations (rho = 0): chi2(1) = 23.41 Prob > chi2 = 0.0000

Appendix

Table A1. Means, standard deviations, distributions of variables

a) Means and standard deviations	Mean	Std.dev.
Training length (natural log)	3.104	1.775
Occupational concentration	0.850	0.168
Wage rate (natural log)	6.082	0.726
b) Dummy variables		
Proprotion of the trainees	0.528	
Proportion of those having university education	0.389	
Proprotion of those having in-school experience	0.323	
c) Training costs are covered by		
Firm	0.463	
Firm and worker	0.092	
Worker	0.445	
Total	1.000	
d) Character of the training programme		
Job-specific	0.451	
General	0.205	
Other	0.344	
Total	1.000	
e) Distribution by types of education		
Agricultural	0.091	
Humanities	0.105	
Foreign languages	0.061	
Small languages	0.003	
Physical education	0.115	
Teacher in primary school	0.007	
Informatics	0.070	
Technical	0.182	
Arts	0.015	
Medical	0.057	
Law	0.044	
Economics&business	0.172	
Social	0.017	
Natural sciences	0.062	
Total	1.000	
f) Firm size		
10 or less	0.135	
10-50	0.266	
51-100	0.164	
101-500	0.198	
501-1000	0.077	
1000+	0.161	
Total	1.000	