Training motivation of low-skilled workers

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Abstract
In the economic literature, several studies have documented the fact that low-skilled workers participate less often in training than high-skilled workers. However, only few empirical studies attempt to explain why this is the case. In this paper, we contribute to the literature by investigating two alternative explanations: 1) low-skilled workers underinvest in training because of the lack of private returns to such investments, i.e. their extrinsic training motivation, 2) low-skilled workers underinvest in training because they lack the intrinsic motivation to participate in training. We show that a lack of intrinsic motivation is more likely than a of extrinsic motivation. Using the Dutch OSA-Labour Supply Panel Study, and controlling for unobserved heterogeneity and endogenous selection into training, we find that low-skilled workers who train earn 1.2% more than those who do not, whereas their probability to become unemployed is 1.8% lower. These returns are not significantly different from the returns for high-skilled workers. Using the ROA-Lifelong Learning Survey covering the years 2004 and 2007, we find that low-skilled workers are significantly less motivated to participate in training. Differences in noncognitive skills (personality, locus of control and future orientation) of high- and low-skilled workers largely explain the differences in intrinsic motivation. In addition, we show that differences in perception of the opportunity costs of training do not play a role in explaining differences in intrinsic motivation of high and low-skilled workers. However, the psychological costs of training (measured as exam anxiety) has a significant negative effect on low-skilled workers’s motivation to participate in training.

Keywords: returns to training, motivation, noncognitive skills

JEL codes: J24, J31, J64, M53

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1 Introduction

The current academic and policy debate stresses the importance of a well-trained workforce. Globalisation and growing international competition raise the need for skill upgrading and innovativeness, whereas the ageing population calls for prevention of skill depreciation due to wear or atrophy (de Grip et al. 2002). Against this background, the European Commission aims to achieve a European competitive and cohesive knowledge society by 2010, where lifelong learning activities play a central role. One of the goals is to reach a training participation rate of at least 12.5% of those aged between 25 and 64. In the economic literature, the fact that low-skilled workers are lagging behind in terms of training participation is well-documented (Bassanini et al. 2005). However, the research attempting to explain this lower training intensity is thin.

The literature suggests that actual participation in training is determined by the firm’s willingness to train and the employee’s willingness to train. In this literature, conflicting assumptions have been made with respect to the possibility for the firm to force employees to participate in training: it is either assumed that they can never force employees to take training (Oosterbeek 1998) or always force them to (Bassinini and Ok 2004). Here, we focus on explaining the differential in training participation between high and low skilled from the workers’ perspective. This perspective is warranted since research has shown that there is no significance difference in firms’s willingness to train low- and high-skilled workers (Leuven & Oosterbeek 1999, Maximiano & Oosterbeek 2007).

In this paper, we contribute to the literature by investigating two alternative explanations: 1) low-skilled workers under-invest in training because of the lack of private returns to such investments, i.e. their extrinsic training motivation, 2) low-skilled workers under-invest in training because they lack the intrinsic motivation to participate in training. Our contribution to the literature is twofold. First, most research focuses on the general returns to training (e.g. wages or employability), yet only a few investigate the heterogeneity in such returns across types of workers (such as low- versus high-skilled). Second, in the majority of econometric models intrinsic motivation is captured by unobserved heterogeneity and is therefore left as a black box. The data we use allows a focus on the specific factors – such as noncognitive skills, opportunity costs and exam anxiety – that trigger the differences in intrinsic motivation to participate in job-related training.
The paper continues as follows. Section 2 presents a brief summary of the existing theoretical and empirical literature on this subject. Section 3 exposes the data and methods used for the analysis. Section 4 discusses the results on the extrinsic training motivation of the low-skilled, while Section 5 focuses on the intrinsic training motivation. Finally, Section 5 concludes.

2 Background

Why do workers participate in job-related training? Early human capital literature already showed that a rational worker applies a cost-benefit analysis to the investment decision in job-related training (Becker 1962). The costs of training mainly concern the costs of study material (if not paid for by the employer) and the opportunity costs of time invested in the training (e.g. foregone earnings, loss of leisure time). The benefits are twofold. First, they consist of higher wages or increased employability, which can be labelled as a worker’s extrinsic motivation to participate in job-related training. Second, a worker can feel better by taking part in job-related training, because he likes to learn, out of curiosity or other reasons. Or better, he is intrinsically motivated to participate in job-related training. Both the costs and the benefits of participation in job-related training are affected by a worker’s background characteristics (e.g. educational attainment), labour market institutions, the employer’s preferences, or other factors. We briefly discuss those most relevant for the training differential between the low- and high-skilled in this section.

Cost of training

With respect to the costs of training, it can be argued that these are higher for the low-skilled. Using the job competition model of Thurow (1975), workers are ranked in a labour queue based on their training costs. The low-skilled have higher training costs compared to the high-skilled because they are less easy to train, i.e. it takes longer for them to master certain skills. In fact, the lower ranking of the low-skilled is due to their lower ability, or cognitive skills, and ability and training can be seen as complements (Acemoglu & Pischke 1999, Heckman et al. 2006).

Extrinsic motivation to training

Labour market imperfections and institutions affect the positive returns to training in terms of a possible wage growth, and create differences in this return between low- and high-skilled workers. Pre-determined wage schemes or minimum wages can remove the wage differential between trained and untrained workers within the same occupation, even within the sector. This reduces the expected returns to training or extrinsic motivation to training for workers, while for the employer it creates
incentives to invest in training, even that producing general skills (Acemoglu & Pischke 1999, 2001). Furthermore, employment protection legislation can increase the expected returns to training, because of higher work security. For both the worker and the employer it raises the incentives to invest in training.

Whether a higher wage after completion of the training is paid, also depends on the willingness to pay such a higher wage by the employer. An employer will only pay a higher wage after a training spell when the training increases the worker’s productivity. In some cases it can be part of an explicit or implicit agreement between the worker and the employer, whereby the worker receives a wage below his marginal product during the training spell and above his marginal product after the training spell, referred to as deferred payment, and usually applied to starting workers (Lazear 1979). The abovementioned predetermined wage schemes or minimum wages limit the use of this deferred payment scheme as a stimulus for training, especially for tenured employees.

In general, no differences in the size of the expected wage returns to training between the low- and high-skilled are predicted by theory. However, the abovementioned minimum wage argument only plays a role at the lower end of the labour market, i.e. only lowering the extrinsic motivation to training for the lowest skilled (only those that remain at the minimum wage level after the training). Additionally, it can be argued that the expected returns for the low-skilled are higher, due to more room for a wage increase compared to the high-skilled, who already have a high wage (ceiling effects).

As for the expected employability as a return to training it can be argued that the employment protection argument favours the returns to training for the high-skilled for whom the dismissal costs are highest. On the other hand, the higher probability to become unemployed for the low-skilled can generate an incentive for them to invest in training (reducing the unemployment probability).

Looking at some empirical evidence, in general a positive relation between participation in training and wage (growth) is observed. The size of this relation, however, differs across studies, depending on the research population, the country or the methodological approach (cf. Büchel & Pannenberg 2004, Booth et al. 2003, Frazis & Loewenstein 2003, Jürges & Schneider 2004, Leuven & Oosterbeek 2004). The observed wage differential between trained and untrained workers varies from 0 to 15.7% (Groot & Maassen van den Brink 2009). It is important to note, however, that most studies analyse the return to training of the average workers, and that the
differences in returns between the low- and high-skilled workers has received little attention. A few studies investigate these differences and the results are again mixed. While Kuckulenz and Zwick (2004) found a smaller return to training for the low-skilled in Germany, Lynch (1992) found no skills-related differences for the US. Moreover, an OECD study shows a larger return to training for the low-skilled in France, the Netherlands and the UK (OECD 1999). Larger returns for the low skilled are also found for Portugal (Budría & Pereira 2007).

Other studies look at the relation between training participation and employability. Sanders and de Grip (2004) find that the Dutch low-skilled workers participate less in job-related training, and that the training facilitates their internal employability within the firm, rather than the external mobility between firms. Other studies find a positive effect of job-related training and the upward labour mobility of the low-skilled, either because of longer tenure, a lower unemployment risk or because of a move to a higher paid job (Blázquez Cuesta & Salverda 2007, Büchel & Pannenberg 2004, Pavlopoulos & Fouarge 2008). The latter effect is found to be stronger for the high-skilled in other studies (e.g. Pavlopoulos et al. 2009), again showing the ambiguity of the relation between training participation and extrinsic returns for the worker.

**Intrinsic motivation to training**

As mentioned, workers might also participate in training because they want to do so, because they feel an intrinsic motivation. It is complicated to disentangle the intrinsic motivation, which is largely driven by personality traits or noncognitive skills, from the worker’s ability or cognitive skills. A further complication is that both cognitive and noncognitive skills determine the worker’s initial education level, and relations become fuzzier when it comes to explaining the relation between initial education, (non)cognitive skills and training participation. It can be argued that there is a direct and indirect effect of intrinsic motivation or noncognitive skills. First, noncognitive skills affect a worker’s cognitive skills. Borghans et al. (2003) have shown that people with favourable noncognitive skills perform best in cognitive tests. Cognitive skills in return largely determine a worker’s education level, as shown by Heckman et al. (2006). Initial education and job-related training are expected to be complementary as mentioned earlier, since higher ability lowers the costs of training. Second, it can be expected that noncognitive skills also directly affect participation in job-related training, i.e. not via a higher education level.

In general, it is then argued that the low-skilled possess less noncognitive skills, or have a lower intrinsic motivation to training participation. On the contrary, it can be argued that the low-skilled might feel a higher need to invest in their human capital in
order to palliate their skills shortcomings and to remain employable in the knowledge economy.

Only few studies are devoted to testing the intrinsic motivation to participate in job-related training, especially in economics. In the majority of studies, mostly psychological, a positive relation is found between intrinsic motivation and training participation, which is in line with the theoretical prediction (Borghans et al. 2009, Maurer & Tarulli 1994, Noe & Wilk 1993). In these studies, again no distinction is made with respect to the education level of the workers. However, Knud (2005) observed that the low-skilled show a subjective feeling of ambivalence toward job-related training, i.e. most of them had negative experiences in school and want to avoid any form of training whatsoever in later life. Their intrinsic training motivation is significantly lower than that of the high-skilled. Tharenou (2001) argued that negative experiences (e.g. failure in taking exams) in the schooling life of the low-skilled can further reduce their intrinsic training motivation.

3 Data and methods

The analyses in this paper are based on three surveys that are representative for the Dutch labour force: the OSA-Labour Supply Panel to study the extrinsic training motivation, and the ROA Life Long Learning Survey and the Dutch Central Bank Survey (DNB Survey) to study the intrinsic training motivation. In all files, we selected working individuals aged 18-64 years-old. We distinguish three levels of skills that are defined in accordance with the highest level of education: low (ISCED 0-1), intermediate (ISCED 2-3) and high (ISCED 4-5).

3.1 Extrinsic training motivation

The OSA-Labour Supply Panel was first held in 1985. Since 1986 it is a biennial panel survey of some 4,500 individuals in about 2,000 households. A key feature is the longitudinal character of the survey: the same survey participants are re-interviewed at each wave of data gathering. We use the waves 1985–2006\(^1\) that are organised as a person-period file. The survey contains information on the individuals and their households, as well as on training participation, the labour market status and wage that are used to investigate the private returns to training investments.

As in most studies (e.g. Bassanini et al. 2005), training is measured as participation in work-related courses in the past two years, and it excludes courses taken for hobby or

\(^1\) At the time of writing, 2006 is the latest available wave of data.
individual general interest. There are, however, some differences in the training question across years. Up to 1992, the question whether or not one participated in training was only asked when the respondent reported that the employer provided such training. Moreover, the 1985 questionnaire asks for training taken in the past, basically since having started paid employment. Finally, the 1986 questionnaire asks for training taken in the past calendar year. In all other years, the references period is the past two years. Despite these differences the pattern of training incidence (as we discuss later in Figure 1) appears to be consistent. However, in econometric models we include year dummies in order to pick these differences in questionnaires.

The labour market status is used as a measure of the worker’s employability: the likelihood of making a transition to unemployment or inactivity at later time points, conditional on being employed in \( t \). The expectation is that training participating in the past two years make such a transition less likely. As a second measure for the extrinsic training motivation, net hourly wages are used, which are computed from the monthly wage and the actual number of weekly working hours. We estimate a random effects probit model for the likelihood of making a transition from paid employment in \( t \) to unemployment in \( t+2 \), as well as a fixed effects wage regression for the effect of training on the hourly wage (see also Pischke, 2001). The models therefore not only allow to control for observed characteristics of the workers, but also for unobserved characteristics – such as differences in motivation or productivity – that could either affect the outcome variables directly, or through the propensity to take part to training.

We estimate the following two models:

\[
pr(u_{it}) = \beta(T_{it} * S_{it}) + X_{it}'\gamma + \delta_t + \varepsilon_{it} \tag{1}
\]

\[
\ln(w_{it}) = \beta(T_{it} * S_{it}) + X_{it}'\gamma' + \mu_t + \varepsilon_{it}' \tag{2}
\]

where \( pr(u_{it}) \) stands for the probability of losing employment between \( t \) and \( t+2 \) for individual \( i \), \( w_{it} \) is the hourly wage of individual \( i \) in year \( t \), \( T_{it} \) is a dummy for training participation in the past two years, \( S \) is the skills level (low, intermediate or high), \( X \) is a matrix of covariates including gender, age, hours worked, paid and unpaid overtime, sector and year dummies. The models are estimated with the inclusion of interaction terms between training participation and education level, so that the parameters of interest in the model that measure the returns to training are contained in the vectors \( \beta \)

\[ We estimate a random effects probit model rather than a fixed effects logit model because the former model makes it possible to compute marginal effects that more easily interpreted.\]
and $\beta'$. The parameters $\gamma, \gamma', \mu, \delta, \epsilon$ and $\epsilon'$ are to be estimated. We estimate [2] using fixed effects wage regression, so $\mu$ represents individual unobserved heterogeneity with $\mu_i \sim N(0, \sigma^2_\mu)$, that is allowed to correlate with the other covariates in the model. We estimate [1] using a random effect probit model, so $\delta$ is a normally distributed random effect.

A problem with estimating the returns to training is that training has been shown to be endogenous (Leuven & Oosterbeek 2008). While this problem is in part addressed by our control for unobserved characteristics, we also include a control for the “pre-programme test” as suggested by Heckman and Hotz (1989). A pre-programme dummy is included in the model. It is equal to 1 in the year prior to training participation, and zero otherwise. In this way, the variable captures systematic differences among participants and non-participants in training. The idea is that such a variable should have no effect on the contemporary wage or labour market status. When it does turn out to be significant, it indicates the presence of self-selection that is not yet accounted for by the model. This pre-programme test, however, can only be applied in the wage regression. The first reason is that up to 1992, the training question was asked conditional on being employed. The second reason is that in all years after 1992, training participation is significantly more likely for employed than unemployed people. Because the pre-programme test requires looking ahead in the data to future training participation, this makes it an unsuitable instrument in the employability regression where the employment status itself is the dependent variable. Alternatively in the model for employability, we use the propensity score matching method (Imbens, 2000). The method consists of estimating the propensity that one will engage into training using the full set of regressors, and use the predicted probability of training (the propensity score) in the outcome model, together with the actual training dummy. The idea is that endogeneity is being picked-up by the propensity score leaving the training dummy as a ‘pure’ measurement of the returns to training. A disadvantage, however, is that the model does not allow correcting for unobserved characteristics.

3.2 Intrinsic training motivation

The effect of intrinsic motivation on training participation is investigated using the ROA Life Long Learning Survey. This survey was fielded in 2004 and 2007 among a representative sample of the Dutch labour force. The data was gathered as part of the CentERdata-panel (Tilburg University), a well-established web-based panel of some 2,000 Dutch households.
The survey contains information on stated preferences with respect to taking part in training that we use to identify differences in training motivation. At the start of both surveys, respondents were asked to report four competences (e.g. flexibility, administrative skills, commercial insight, people skills, etc.) that are important to do their job successfully. These competencies were to be picked out in a list of 26 competencies. Later in the questionnaire respondents were asked which of these four competencies they would prefer to train if a course was provided to them during working time and at the employer’s expenses. Then, the question was asked whether they would take their preferred course if they had to invest one evening of their leisure time during half a year. Respondents could answer on a five-point scale with the categories ‘very unlikely’, ‘a small chance’, ‘50-50’, ‘a large chance’, ‘very likely’. Because respondents indicated that the skill is important for their job and that they would rather train this particular skill rather than other skills, the answers to this last question can be interpreted as the respondent’s intrinsic motivation to train.

We model the likelihood that one chooses to participate in training using an ordered probit model:

$$\text{pr}(tr = j) = \Phi(S_i, X_i, N_i, C_i, \alpha_j)$$

where the dependent variable indicates the respondent’s answers to the training question ($tr$), with $j$ taking any of five values for ‘very unlikely’, ..., ‘very likely’. $\Phi$ denotes the cumulative standard normal distribution, and $\alpha_j$ denotes the threshold points. The model controls for the skills level ($S$) and a number of background characteristics ($X$): gender, age, sector of industry and survey year. In addition, the models control for individual differences in noncognitive skills ($N$) – i.e. economic preferences and personality traits – as well as the opportunity and psychological costs of training ($C$). In most econometric models the effect of such variables is assumed to be captured in unobserved heterogeneity. With our analysis, we demonstrate the explicit contribution of non-cognitive skills and perceived opportunity and psychological costs of training in explaining the training differential of the low- and high-skilled.

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3 Interestingly, the top three of most important competencies is the same, irrespective of the skills level: ‘people skills’ is the most frequently reported competence, followed by ‘occupation-specific skills, and ‘communication skills’.
The opportunity and psychological costs of training are derived from two questions that follow the training question in the 2004 ROA Life Long Learning Survey. The questions ask for what would be the reason why one would choose not to follow the training, and were asked irrespective of the answer to the training question: 1) ‘I prefer to do something else in the evening’, and 2) ‘I find it scary to take an exam again’. Answers could be given on a seven-point scale ranging from ‘disagree completely’ to ‘agree completely’. While the first statement refers to the opportunity cost of training, the second refers to the psychological cost of training. Both statements can help increase our understanding of the training differential between low- and high-skilled workers.

Economic preferences and personality traits are available in a different survey – the DNB Survey – that could be matched to our data at the individual level, since it is also fielded among the CentERdata-panel respondents. We use several modules of the DNB Survey (i.e. 2004, 2005 and 2007) to measure two types of economic preferences (locus of control and future orientation), as well as personality traits. Locus of control is measured in the 2005 and 2007 waves using 13 questions such as: ‘My life is determined by my own deeds’, ‘I am able to determine my personal interests’, ‘It is a matter of chance whether I become rich or poor’. The questions were to be answered on a seven-point scale ranging from ‘completely disagree’ to ‘agree completely’. We used factor analysis to construct a single indicator for the locus of control: increasing values reveal a stronger internal locus of control. Future orientation is measured in the 2004 and 2007 waves using 12 questions such as: ‘I want to sacrifice well-being now in order to obtain better results later’, ‘I am often busy with things that will only have consequences in the future’, ‘I only think about the direct consequences of the actions I take’. Answers could be given on a seven-point scale ranging from ‘does not at all apply to me’ to ‘really applies to me’. We applied factor analysis in order to derive one single underlying factor of future orientation. Higher values indicate a stronger future orientation. Personality traits are assessed in the 2005 survey with 50 questions aiming at measuring the five underlying dimensions of the Big Five taxonomy (Goldberg, 1971). Factor analysis, again, is used to derive the five personality traits openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism.

The factors derived from the DNB Survey for 2004 and 2007 are matched to the corresponding respondents in those years. Factors derived from the 2005 DNB Survey are matched to the 2004 respondents of the ROA Life Long Learning Survey. Despite

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4 We used principal-component factor analysis, with varimax rotation.
the fact that both datasets pertain in principle to the same set of respondents, in a limited number of cases no match for the ROA Life Long Learning Survey respondents could be found in the DNB Survey. Of the 1,290 working individuals of the 2004 ROA Life Long Learning Survey, 217 cases could not be matched to the 2004 DNB Survey, and 276 cases could not be matched to the 2005 DNB Survey. Of all 941 working individuals in the 2007 ROA Life Long Learning Survey, 106 cases could not be matched to the 2007 DNB Survey. For these cases that could not be matched, we set the factors measuring non-cognitive skills equal to zero and include a dummy variable in the models indicating whether or not the factor is missing.

The analyses using the Big Five taxonomy and the opportunity and psychological costs of training are constrained to the 2004 wave of the ROA Life Long Learning Survey.

4 Training participation and returns to training

4.1 Training participation

In 2006, 44% of all workers report having followed one or more trainings in the past two years. However, this percentage differs significantly across skills levels (Figure 1). More than half of the high-skilled workers (53%) report training participation in the past two years, while the corresponding percentage among the low skilled is only 30%. The training incidence of workers with an intermediate skills level is 44% in 2006.5 The training participation follows the same increasing pattern in the period 1986–2004 for all skills levels. However, the difference in training incidence among low- and high-skilled workers, but also the difference between intermediate- and high-skilled workers, has been increasing since 1996. The drop in training incidence between 2004 and 2006 is confirmed by other statistical sources (Borghans et al., 2009), while the drop between 1985 and 1986 is due to differences between the questionnaires.6

5 In 2006, the number of training courses taken in the past two year is not significantly different for the three skills level.
6 The 1985 questionnaire asks for training followed in the past, basically since having started paid employment. The 1986 questionnaire asks for training followed in the past calendar year. In all other years, the references period is the past two years. Econometric models include year dummies in order to pick these differences.
4.2 Returns to training

Figures 2 and 3 show to what extent training contributes to enhancing employability and increasing wages, respectively. Figure 2 depicts the probability of losing employment (becoming unemployed or inactive) in a ten-year period for workers with and without training. The figure shows that workers who did invest in training in the past two years are less likely to lose employment in the years that follow compared to workers who did not invest in training. The difference in unemployment probability is on average some 5 percentage point after two years, and it increases to 8 percentage points after six years. However, the difference in the probability of losing employment between those who train and those who don’t is larger for low- than for high-skilled workers. For low-skilled workers who did not follow training the probability of losing employment between $t$ and $t+10$ is 24%, while the probability for those who did follow training is 14%. The corresponding percentages for high-skilled workers are 14% and 11%, respectively.

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7 In Figure 2 and 3, the age selection is such that it excludes individuals who reach the official pension age of 65.
Figure 2: Probability of losing employment with and without training between $t$ and $t+2$, by skills level (percentages)

Source: OSA-Labour Supply Panel.

Figure 3 shows that training not only increases employability, but also wages. The figure shows the evolution for workers with and without training in the past two years, where the wage in $t$ is normalized to 100. For the low skilled, the effect of training on the wage is immediate: already after two years workers with training earn a higher wage than workers without training. This is consistent with the fact that low-skilled workers more often report having taken a course because their employer wanted them to do so, possibly making it possible for them to be promoted to high wage positions. Also in later year, the wage premium for taking training is larger for the low skilled. The effect of training on the wage of high-skilled workers is comparatively small, which could be explained by the fact that high-skilled workers follow courses to maintain their human capital (rather than to increase it), and that their reward for training investments could take other forms than higher wages.
Figure 3: Hourly wage of workers with and without training between $t$ and $t+2$, by skills level

Table 1 reports the estimation results of random effects probit regressions for the probability of losing employment between $t$ and $t+2$, and of a fixed effects panel wage regression. For low-skilled workers who took one or more trainings in the past two years, the probability of losing one’s job is 1.8 percentage point lower than for the low skilled who did not participate in training. Despite the fact that high skilled have overall a lower probability of exiting paid employment, whether or not they followed training does not appear to matter more for them than it does for low-skilled workers. Since the random effects probit model does not control for endogeneity (unobservables are assumed not to be correlated with the observables, among which the training dummy, and the setting is unsuitable for the pre-programme test), we use the propensity score matching instead to control for endogeneity (column 2). The model suggests larger employability returns to training: the probability of losing employment is 2.8% lower for workers who take training. However, this model does not control for unobserved individual characteristics that affect the employment probability. Henceforth, this estimate is likely to overstate the effect of training. However, also with this model we conclude that the returns for the low skilled are not different from the returns for the other skills levels.
Table 1: Effect of training participation on employability and wage\(^1\)

<table>
<thead>
<tr>
<th></th>
<th>Probability of leaving paid employment between (t) and (t+2) (^2)</th>
<th>Hourly wage (in log)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Panel probit, RE Propensity score model (^3)</td>
<td>Panel FE model</td>
</tr>
<tr>
<td>Training in past 2 years</td>
<td>-0.018*** ((0.005)) -0.028*** ((0.005))</td>
<td>0.012* ((0.007))</td>
</tr>
<tr>
<td>Training * Intermediate skilled</td>
<td>(0.009) (0.009) (0.009) (0.009)</td>
<td>(0.009) (0.009) (0.009) (0.009)</td>
</tr>
<tr>
<td>Training * High skilled</td>
<td>-0.012 ((0.009)) 0.004 ((0.010)) -0.009 ((0.010)) -0.018 ((0.010))</td>
<td>(0.010) (0.010) (0.012) (0.012)</td>
</tr>
<tr>
<td>Intermediate skilled</td>
<td>-0.005 ((0.004)) 0.003 ((0.010)) -0.005 ((0.010)) -0.005 ((0.012))</td>
<td>(0.010) (0.010) (0.012) (0.012)</td>
</tr>
<tr>
<td>High skilled</td>
<td>-0.010* ((0.005)) 0.046*** ((0.014)) 0.035* ((0.018))</td>
<td>(0.014) (0.018)</td>
</tr>
<tr>
<td>Propensity score</td>
<td>-0.258*** ((0.013))</td>
<td>-0.002 ((0.008))</td>
</tr>
<tr>
<td>Pre-programme test</td>
<td>\textbf{Chi-squared} 618.561 636.097</td>
<td>13617 8200</td>
</tr>
<tr>
<td>\textbf{df}</td>
<td>33 4</td>
<td></td>
</tr>
<tr>
<td>\textbf{Loglikelihood}</td>
<td>-3972.757 -4429.542</td>
<td>12196.692 8174.004</td>
</tr>
<tr>
<td>\textbf{N}</td>
<td>20148 20148</td>
<td>31145 19657</td>
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<tr>
<td>\textbf{Sigma_u}</td>
<td>0.335 0.385</td>
<td>0.385 0.382</td>
</tr>
<tr>
<td>\textbf{Sigma_e}</td>
<td>0.218 0.209</td>
<td>0.218 0.209</td>
</tr>
<tr>
<td>\textbf{Rho}</td>
<td>0.101 0.757</td>
<td>0.757 0.770</td>
</tr>
</tbody>
</table>

\(^1\) Additional control variables: gender, age, age squared, hours worked, unpaid overtime work (dummy), paid overtime work (dummy), sector dummies, year dummies.

\(^2\) Marginal effects from probit estimates.

\(^3\) In the propensity score model, the covariates are only included in the probit model to calculate the propensity that one will engage in training.

\(* p<0.10\), \(** p<0.05\), \(*** p<0.01\). Standard errors in parentheses.

Source: OSA-Labour Supply Panel.

The wage returns to training participation are estimated to equal 1.2\% (Table 1). In the wage regression that includes the pre-programme test, the returns are slightly higher (1.6\%) but the difference between the two estimates is not statistically significant. Moreover, because the pre-programme test is not significant, we conclude that self-selection is sufficiently controlled for in the fixed effects panel wage regression. The results in the table also imply that the wage returns to training are not different across skills levels.

All in all the results in Table 1 show that there are positive private returns to training for the low skilled, and that these returns are not any different from the returns of workers with higher skills attainments. Assuming that the direct costs of training are the same for low- and high-skilled workers, this suggests that poor returns to training is not a potential explanation for the training differential depicted in Figure 1.

5 Intrinsic training motivation noncognitive skills

In order to investigate the motivation to train, we turn to analyses of the matched ROA-Life Long Learning Survey and DNB Household Survey (see Section 3.2).
First, we discuss the answers to the hypothetical, but realistic training intention question for the three skills levels. Because the question is conditional on the respondents stating the skill as relevant for his or her job, the answers can be thought of as indicative of training motivation. Remember that the answers are measured on a scale ranging from “very unlikely” (1) to “very likely” (5). On average low-skilled workers are less inclined to participate in training than high-skilled workers. The mean value for the answer of low-skilled workers is 2.8, while it is 3.2 for high-skilled workers. Workers with an intermediate skills level score 3.1.

Table 2 reports the model estimates for the intrinsic motivation to train. Several models were tested. Model 1 is the base model that only controls for skills level and background characteristics, while model 2 in addition controls for economic preferences. Model 3 controls, in addition, for opportunity and psychological costs of training. Model 4 includes the full set of noncognitive skills, including the Big Five indicators. Because Models 3 and 4 could only be estimated on the 2004 survey, we also report the outcome from the basic model for the 2004 sample only for the purpose of comparison (Model 5).

The estimates of Model 1 reveal that training intentions are higher for intermediate-skilled workers compared to low-skilled workers, and even higher for high-skilled workers. However, the coefficient for intermediate-skilled workers is significantly lower than that of high-skilled workers. Because the training pertains to relevant skills, and because the returns to training are similar across skills levels, we conclude that low-skilled workers are less motivated to train.

The inclusion of economic preferences (Model 2) results in lower estimates for the effect of skills differences on training intention. Economic preferences do have a significant effect on the propensity to train. Workers with stronger future orientations have stronger intentions to train, suggesting that they perceive training as an investment strategy. Workers with a stronger internal locus of control also have stronger intentions to train, suggesting that they take their fate in their own hands and invest in their human capital to secure their labour market position.

Controlling for perceived opportunity and psychological costs of training (Model 3) further decreases the size and the significance of the skills differences in training intentions. High costs result in lower intentions to train, and the effect of psychological costs (exam anxiety) is particularly large compared to the effect of opportunity costs.
Controlling for the full set of personality traits and economic preferences (Model 4), we find that conscientiousness is positively correlated with training intentions. Moreover, when controlling for these characteristics, both the size and the significance of the skills dummies is reduced: the effect of high skills is no longer significant, and the effect of intermediate skills is reduced and only significant at the 10%-level. The findings reported in Table 2 suggest that interpersonal differences in noncognitive skills to a large extent explain the skills-related differences in the motivation to train.

Table 2: Ordered probit regression for the likelihood that one would take part to training

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average education</td>
<td>0.222***</td>
<td>0.197***</td>
<td>0.158*</td>
<td>0.148*</td>
<td>0.161*</td>
</tr>
<tr>
<td></td>
<td>(0.070)</td>
<td>(0.070)</td>
<td>(0.087)</td>
<td>(0.088)</td>
<td>(0.084)</td>
</tr>
<tr>
<td>High education</td>
<td>0.315***</td>
<td>0.255***</td>
<td>0.170*</td>
<td>0.132</td>
<td>0.229***</td>
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<tr>
<td></td>
<td>(0.069)</td>
<td>(0.070)</td>
<td>(0.089)</td>
<td>(0.090)</td>
<td>(0.085)</td>
</tr>
<tr>
<td>Future-orientation</td>
<td>0.071**</td>
<td>0.082**</td>
<td>0.081**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.039)</td>
<td>(0.040)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Internal locus of control</td>
<td>0.126***</td>
<td>0.160***</td>
<td>0.154***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.040)</td>
<td>(0.043)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Opportunity costs</td>
<td>-0.123***</td>
<td>-0.126***</td>
<td></td>
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<tr>
<td></td>
<td>(0.021)</td>
<td>(0.021)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Exam anxiety</td>
<td>-0.266***</td>
<td>-0.266***</td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>(0.023)</td>
<td>(0.023)</td>
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<tr>
<td>Openness</td>
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<tr>
<td></td>
<td>(0.039)</td>
<td></td>
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<tr>
<td>Conscientiousness</td>
<td>0.083**</td>
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<tr>
<td></td>
<td>(0.041)</td>
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<tr>
<td>Extraversion</td>
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<tr>
<td></td>
<td>(0.040)</td>
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<tr>
<td>Agreeableness</td>
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<td></td>
<td>(0.041)</td>
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<tr>
<td>Neuroticism</td>
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<td></td>
<td>(0.040)</td>
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<tr>
<td>Pseudo-R-squared</td>
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<td>0.036</td>
<td>0.111</td>
<td>0.113</td>
<td>0.008</td>
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<tr>
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<td>2161</td>
<td>1224</td>
<td>1224</td>
<td>1224</td>
</tr>
</tbody>
</table>

1) Regression coefficients. Models 3 and 4 could only be estimated on the 2004 wave of the ROA-Life Long Learning Survey.
2) Additional control variables: gender, age, age squared, sector of industry, dummy for 2007 wave (model 1 and 2 only), and 4 threshold points.
*p<0.10, **p<0.05, ***p<0.01. Standard errors in parentheses.

6 Conclusion and discussion

The low training participation rate of low-skilled workers relative to high-skilled workers is well documented in the empirical economic literature. However, a clear explanation for this difference in training incidence is lacking. This paper contributes
to filling this gap by investigating two alternative explanations: 1) low-skilled workers underinvest in training because of the lack the extrinsic training motivation, i.e. their private return to such investments is too low; 2) low-skilled workers underinvest in training because they lack the intrinsic motivation to participate in training. We investigated both explanations using Dutch data. After controlling for unobserved heterogeneity and endogeneous selection into training, we find that low-skilled workers who train earn 1.2% more than those who don’t, whereas their probability to become unemployed is 1.8% lower. Moreover, these private returns do not appear to be any different from the returns high-skilled workers derive from taking part to training. This suggests that the difference in returns to training can not explain the differences in training participation between low- and high-skilled workers.

Using data on intentions to participate in training that is perceived to be relevant for one’s job but that requires some amount of time investment from the worker, we find that low-skilled workers are significantly less willing to participate in training compared to high-skilled workers. Because the training is self-reported as relevant and because the returns to training have been shown to be equal across skills levels, this lower readiness to train suggests a lower intrinsic motivation to train.

In an attempt to better understand what is driving this difference in training motivation across skills groups, we show that it can to a large extent be explained by differences in noncognitive skills such as someone’s conscientiousness, economic preferences (locus of control and future orientation), and differences in perceived costs aspects of training: the opportunity costs (rather devote time to other activities) and the psychological costs (exam anxiety). An implication is that making it more accessible for low-skilled workers to take exams for the training followed could increase their participation in adult learning.

**Literature**


