Term Paper Proposal

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This is where we put the abstract...

Introduction

What is the topic of your dissertation? What were the reasons for choosing this topic? What is your **research hypothesis**? How do you define the central terms of your hypothesis? Why and for whom is it important to answer these questions?

- Motivate (one paragraph).
- Summarize what we know (one paragraph).
- Third paragraph: Tell us what you are doing!
- Describe research design.
- Value added.
- Summarize key findings.
- DO NOT write a "roadmap".
- No subsections in the Introduction

Literature

(We contribute to the literature on digitalization, job tasks, training, and job mobility.)

Computer capital and workers that perform routine tasks are substitutes whereas computer capital and workers that perform non-routine cognitive tasks are complements (Autor et al., 2003). The declining price of computer capital has led to a U-shaped labor demand function (Acemoglu and Autor, 2011; Autor and Dorn, 2013). This indicates that middle-skilled workers were replaced by technology while the demand for high skilled workers and low-skilled workers has grown. Autor and Dorn (2013) show that increased employment at the lower tail of the earnings distribution is mainly due to an increase in service occupations. At the upper tail technological changed led to a college wage premium: wages of college graduates relative to high-school graduates increased

(Acemoglu and Autor, 2011). De La Rica et al. (2020) develop abstract, routine and manual task measures and find that a one-standard-deviation increase in abstract tasks is related to a 3.3-log-point wage premium. For each standard deviation of routine tasks there is a 2.6 to 2.9-log-point wage penalty.

This vast literature on the change of job tasks has mainly focused on wage effects and takes skills of workers as pre-defined. However, workers and firms could also invest in new skills via training.

Becker (1962) distinguished between two kinds of on-the-job training: specific and general. Specific training increases the marginal product of a worker within one specific firm while general training increases her productivity in many other firms. In a perfect labor market workers are paid their marginal product. In such case, firms would not invest into general training of their employees as they could leave the firm and look for a better paid job. Instead, workers would pay for their general training as an investment into higher future wages. Acemoglu and Pischke (1999) argue that firms still invest in general training due to their monopsony power. Wages increase by less than the marginal productivity and firms can profit. Konings and Vanormelingen (2015) find that an increase in the share of trained work-ers by 10 percentage points raises the productivity by 1.7 to 3.2 percent while wages only increase by 1.0 to 1.7 percent.

Evidence on job mobility behaviour of workers is more mixed. Zweimüller et al. (2003) findings support Becker (1962) human capital theory. Workers who received firm specific training quit less often and show less job searching behaviour. Workers who received general training increased their job searching activities and quit more often. Dietz and Zwick (2020) use German employer-employee data and find that training increases the retention probability. These studies focus on on-the-job training.

Lynch (1991) and Lynch (1992) compares on-the-job to off-the-job training. She focuses on young workers that are particularly mobile. She finds that on-the job training tends to be firm specific in the US and thus wage raises cannot be taken along to subsequent employers. Off-the-job training by proprietary institution have little effect on wages in the current employment but raise future expected wages in subsequent employment. Lynch (1991) shows that the probability of leaving an employer varies with respect to race, gender, and educational level. Workers with disabilities, black workers and workers with a high school degree or less increased the probability of leaving the first employer. Working in a job with collective agree-ment or having a college degree decreased their probability of leaving the employer. The effect of training, disability, and education disappears when Lynch (1991) re-estimates the equation only for men, while these effects are particularly strong for women.

Applying a machine learning approach permits us to take a broader approach on this topic. Instead of restricting our estimation to a specific group of workers or countries, we identify the factors that drive the probability of leaving-a-job and job-switching from a set of ## variables.

- mostly effect on wages, inequality

Data

What is the epistemological framework of the dissertation? For empirical studies it should be made clear: Why were the specific methods of data analysis chosen? How was the data acquired?

To explore these questions we use the results of the survey of the Programme for the International Assessment of Adult Competencies (PIAAC) (GESIS - Leibniz Institute for the Social Sciences (n.d.)). The survey was conducted by the Organisation for Economic Co-operation and Development (OECD) with the goal to assess which skills adults need to manage challenges and tasks at work as well as in their personal life. The study targeted explicitly the skills in literacy, numeracy and adaptive problem solving while also comprising comprehensive background information on the respondents past and current education, subjective assessments of their skills and job requirements as well as information on migration (GESIS - Leibniz Institute for the Social Sciences (n.d.)). The first cycle consisted of three rounds and began in 2011/12. In the first round 24 countries took part. In the second round nine additional countries participated and in the last round individuals from five different countries were questioned. In total 40 countries participated in the first cycle comprising about 5,000 randomly selected adults who were between 16 and 65 years old. The second cycle started in 2018 and results are to be expected in 2022 (GESIS - Leibniz Institute for the Social Sciences (n.d.)).

For the study at hand the results of the first wave are used in a reduced form. The original dataset comprises 1,460 columns with 230,691 observations of respondents. However, the 'research question of this paper is to analyze the probability of trainings for middle-skilled workers compared to trainings for high-skilled and low-skilled workers in the wake of the increasing polarization of skills following from digitization'. To answer this, the original PIAAC dataset is reduced to 130 variables in total, including indices. For example, information on the various test results conducted in the study are excluded. To achieve comparability across countries, questions which were only answered by respondents living in the United States are also excluded. The final dataset is cross-sectional with one observation representing the answers of one respondent.

The 130 variables we kept in the final dataset comprise information on the individual's background information, her past and ongoing formal or informal education, information on training activities, information on ICT skills and the respective extensive and intensive margin, her subjective job requirements, information on her curent job and information on monthly income. As we do not restrict the dataset in terms of respondents but only in terms of questions answered, our final dataset comprises 230,691 observations of individuals. Of those 230,691 individuals, 122,830 are female and 107,859 are male (see Figure 1). The age of the respondents is evenly distributed between the ages 16 to 64 with a female mean age of 39.95 years and male mean age of 39.38 (see Figure 2).
The classification of the respondents jobs in terms of skills is also evenly distributed across age groups and gender. However, respondents working in semi-skilled white-collar occupations are slightly younger than those working in skilled occupations or semi-skilled blue-collar occupations (see Fiugre 3).

The key variables of this study are the the skill classification of the individual's job and her trainings comprising on-the-job training, seminars or workshops, distance or open training courses as well as private lessons. The simple OLS regressions reveal that there are positive correlations between the high-skilled jobs and the number of trainings respondents participated in. This holds true for on-the-job-training, seminars or workshops, distance or open educational training as well as for private lessons. However, for semi-skilled jobs, the picture is slightly different. Here, the number of seminars or workshops and private lessons are positively correlated with the semi-skilled occupations.

- Name, source, unit, time, structure, number of observations, relevant population.
- Definition of (main) sample.

Figure 1: Distribution of Gender

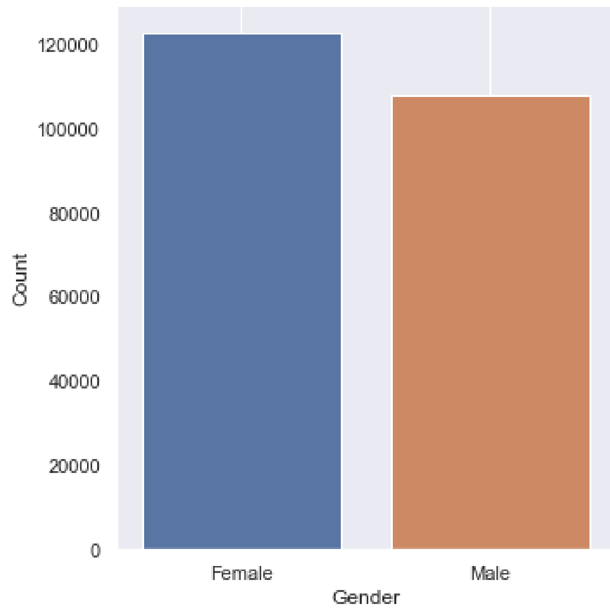


Figure 2: Distribution of Age

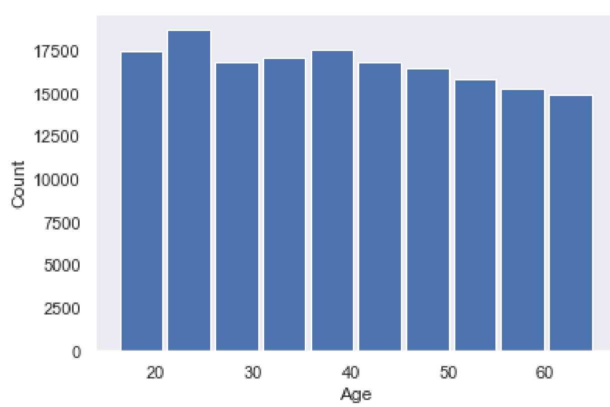
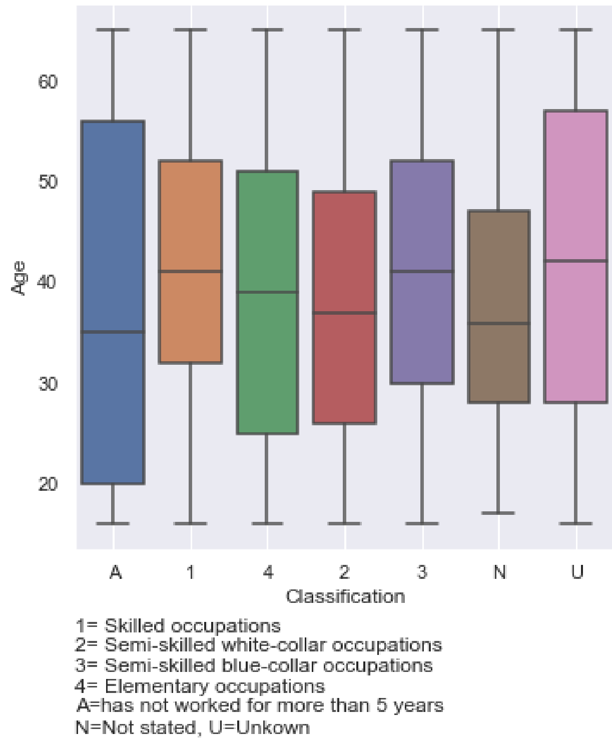


Figure 3: Age and Classification of jobs



- Definition and characteristics of key variables.
- Limitations and potential biases.
- Provide the data and the software code (replication).
- Plot the main empirical associations you want to study!
- Do NOT assume the reader knows anything about these data

Lasso Linear Model

We start with a simple linear regression model $y = X\beta + \varepsilon$, where $y \in \mathbb{R}^N$ is the predicted participation in on-job or off-job training, $X \in \mathbb{R}^{N\times k}$ are the vectors of covariates, and $\varepsilon \in \mathbb{R}^N$ is the residual with the standard assumptions of OLS. To select the set of covariates with the strongest predictive power from our set of $\ldots$ variables, we apply the Least absolute shrinkage and selection operator (Lasso) that was first proposed by Tibshirani (1996). We add the Lasso penalty equal to $\sum_k |\beta_k|$ to our linear model. The Lasso linear estimator $\hat{\beta}$ is then given by

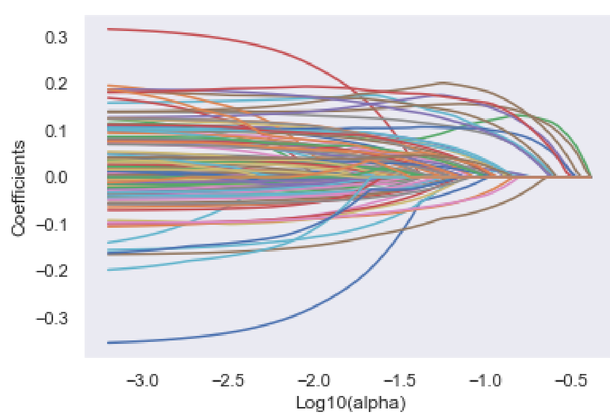
$$\hat{\beta}_\lambda = argmin\{\sum_i (y_i - x_i^T \beta)^2 + \lambda \sum_k |\beta_k|\} \tag{1}$$

That is, we minimize the sum of squared residuals but the Lasso penalty puts a cost at every $\hat{\beta} \neq 0$ and thus, we penalize complexity and avoid over-fitting the model. $\lambda > 0$ is the penalty weight or the *tuning parameter*.

Training the Model

Figure 4 and Figure 5 show the lasso regularization path of candidate models $\hat{\beta}_1 \ldots \hat{\beta}_t$ that we obtained by minimizing Equation 1 over a sequence of tuning parameters $\lambda_1 < \lambda_2 < ... < \lambda_T$ with on-job training and off-job training as dependen variable respectively. The vertical axis contains different levels of $\hat{\beta}$. The horizontal axis contains different levels for λ. Each vertical section along the horizontal axis, represents one candidate model. Moving from higher to lower λ, the algorithm includes more nonzero $\hat{\beta}_k$ and becomes more complex. To find the optimal value for λ we use *5-fold cross validation*. We split the data in 5 random evenly sized subset and derive the lasso paths $\hat{\beta}_1^k \ldots \hat{\beta}_T^k$ on each of the folds but one fold to train the models. Then we use the left out fold to obtain the out-of-sample error for each candidate model. The best $\hat{\lambda}_t$ minimizes the out-of-sample error.

Figure 4: Lasso path for on-job training



describe optmal λ and p* here

Figure 5: Lasso path for off-job training

Variable Selection

present most important variables here

Out-of-Sample Evaluation Results

present out of sample performance and compare to OLS

Lasso Logistic Model

We now estimate the Lasso model for the binary oucome variables of whether or not a person received on-job training and whether or not a person participated in an off-job training. We estimate the Lasso-regularized logistic model for the probability that a person received one specific training as follows:

$$\hat{\theta}_{\lambda} = argmin(-l_N(\theta)) + \lambda \sum_k |\theta^k| \tag{2}$$

where $l_N(\theta))$ is the log-likelihood function

$$l_N(\theta)) = \sum_i [y_i x_i \theta - log(1 + e^{x_i \theta})]$$

$\sum_k |\theta^k|$ is the lasso penalty that shrinks coefficients of little explanatory power to zero. $\lambda > 0$ is the penalty weight.

Training the Model

Figure 6 and Figure 7 present the Lasso regularization path for the logistic candidate models. The models are ordered from the most penalized to the least penalized model and the algorithm includes more non-zero coefficients in the model. We select λ by a *5-fold cross calidation* process. This yields an optimal Lasso penalty of 1.6238 for on-job training and 1.62 for off-job training.

Figure 6: Logistic model: Lasso path for on-job training

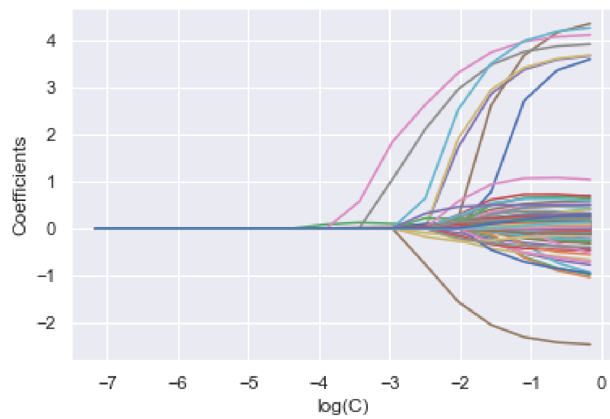
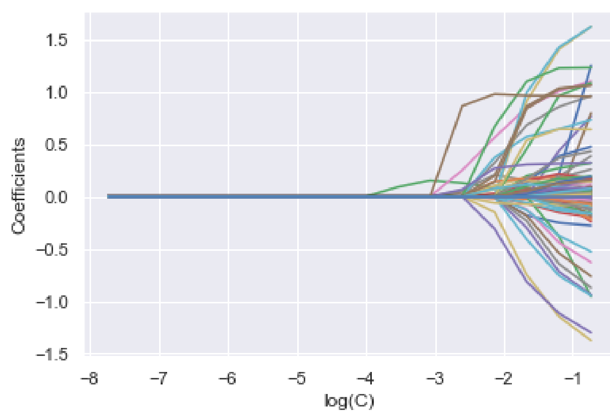


Figure 7: Locistic model: Lasso path for off-job training



Variable Selection

The Lasso logit model indentifies 145 columns[1] with non-zero predictive power for on-job training. We present the coefficients in Table . Let us first turn to the results for the skill level. *skill_4* are elementary occupations and represent the reference group here. *skill_3* is the dummy variable

[1]Including country and industry controls

for semi-skilled blue-collar occupations, *skill_2* is the dummy for semi-skilled white-collar occupations, and *skill_1* is the dummy for skilled occupations. Working in a semi-skilled blue-collar occupation increases the probability of receiving training by or white-collar occupation compared to working in an elemetary occupation has no effect on the probability of receiving training. But working in a skilled occupation increases the probability of receiving training by 9.3~% relative to working in an elementary occupation.

The dummy variable for whether a person was employed during studying for a qualification, *b_q10a_Yes*, has the highest positive explanatory power. If a person uses a computer on this specific job (*g_q04_Yes*), it increased the probability of receiving on-job training by 64.23~%. Having general computer experience (*computerexperience_Yes*) increases the probability of receiving on-job training by 43.11~%. People are 25.79~% more likely to participate in on-job training, if they have the feeling that they need more training in order to cope well with their present duties (*f_q07b_Yes*). Moreover, employees are more likely to receive training if they work in larger companies, compared to smaller companies and if they have a higher educational level.

If a job does not involve keeping up to date with new services and products (*d_q13c_Never*), it lowers the probability of reveiving training by 33.37~%. Never participationg in online discussions such as conferences (*g_q05h_Never*) reduces the probability of receiving on-job training by 37.38~%. Also, having a low education level, if a job needs less than one month of prior work experience, and working in a job without a contract have the most negative effects on the chances of participating in on-job training.

For off-job training, the Lasso logit model identifies 138 non-zero columns[2] The results look very similar to the on-job training. Working in a skilled occupation increases the probability of participating in open education by 9.14~%. The indicator for semi-skilled white-collar workers is also positive but with a magnitude of 0.0861~% very small. As in on-job training, the most important feature is being employed and using the computer on this specific job (79.04~%) or having general computer experience (63.8~%). Also working in a larger company and having a higher educational level increases the probability of participating in open education. Lower education, having no contract, and never using the computer for work tasks negatively effect the probability of participating in open education.

[2] Including country and industry controls

Accuracy of the Model

Finally, we evaluate the accuracy of the Lasso logit model. Figure 8 presents the confusion matrix for on the job training. 10941 are true negative prediction and there are 85 true positive predictions. The model yields 1203 false negative predictions and 56 false positive predictions. We present the confision matrix for open education in Figure 9. For this model, we obtain 10940true negative predictions and 84 true negative predictions. 1204 + 57 are incorrect predictions.

Figure 8: Logistic model: Confusion matrix for on-job training

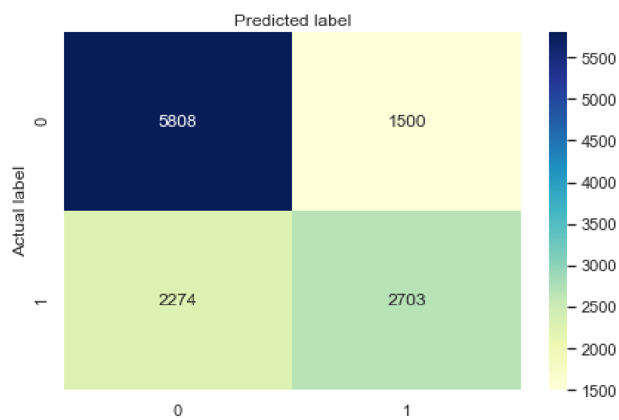
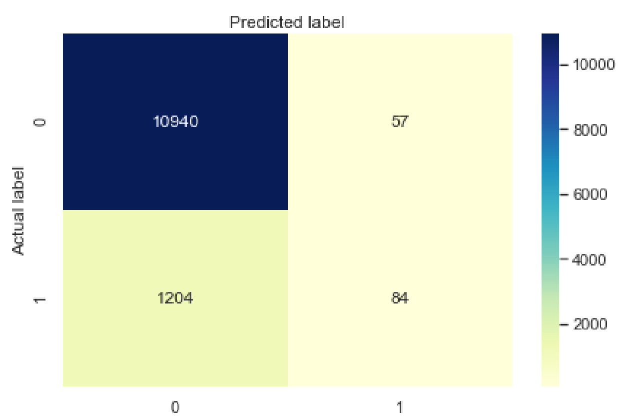


Figure 9: Locistic model: Confusion matrix for off-job training



In Table

Table 1: Accuracy of the Lasso logistic model

	Lasso Logistic Model	Logistic Model
On-job training		
Training accuracy	0.7886	0.4987
Test accuracy	0.7822	0.5067
————————:	————————:	:——————-
Off-job training		
Training accuracy	0.7950	0.4987
Test accuracy	0.7892	0.5067

- Describe how the hypothesis is linked to your estimation.
- Describe the estimation using equations.
- Discuss the parameters and variables.
- What are the identifying assumptions, what are (possible) violations and their consequences?
- What will you do about this?
- Tell a story!
- Guide the reader.
- Focus on the key points, not the details.
- Discuss quality and quantity.
- Discuss problems.
- Compare to the literature.

Further steps

Which results can be expected? What is new? Where lies the progress for science? In what way can scientific discussion proceed / be stimulated by the thesis?

(APPENDIX) Appendix

Appendix: Tables

Table: Lasso logistic regression for on-job training

	Coefficients	Feature
0	-0.016459	age_r
1	0.0166996	j_q03b
2	0.0205559	yrsget
3	0.00927976	c_q09
4	0.00388655	c_q10a
5	0.0559252	readytolearn
6	-2.07843e-07	earnmthallppp
7	0.0831342	gender_r_Male
8	-0.0149177	d_q13c_Every day
9	-0.178626	d_q13c_Less than once a month
10	-0.127389	d_q13c_Less than once a week but at least once a month
11	-0.556924	d_q13c_Never
12	-0.0336161	pared_At least one parent has attained tertiary
13	-0.0500042	pared_Neither parent has attained upper secondary
14	0.0547907	b_q01b_Engineering, manufacturing and construction
15	-0.140491	b_q01b_General programmes
16	0.186053	b_q01b_Health and welfare
17	-0.110284	b_q01b_Humanities, languages and arts
18	0.0208533	b_q01b_Science, mathematics and computing
19	-0.138746	b_q01b_Services
20	-0.00921516	b_q01b_Social sciences, business and law
21	0.157079	b_q01b_Teacher training and education science
22	-0.539921	leaver1624_Not in education, did not complete ISCED 3, aged 16 to 24
23	0.62975	g_q04_Yes
24	-0.343033	d_q03_The private sector (for example a company)
25	-0.0724431	d_q03_The public sector (for example the local government or a state school)
26	-0.0535022	g_q05e_Every day
27	0.0610249	g_q05e_Less than once a month
28	0.0544428	g_q05e_Less than once a week but at least once a month

	Coefficients	Feature
29	-0.0425196	g_q05e_Never
30	0.0986375	d_q04_t_Employee, supervising fewer than 5 people
31	0.248781	d_q04_t_Employee, supervising more than 5 people
32	0.00296429	d_q09_A temporary employment agency contract
33	0.0628857	d_q09_An apprenticeship or other training scheme
34	0.132835	d_q09_An indefinite contract
35	-0.521933	d_q09_No contract
36	0.0733041	d_q09_Other
37	0.0829767	g_q05a_Every day
38	-0.0931355	g_q05a_Less than once a month
39	0.0578459	g_q05a_Less than once a week but at least once a month
40	-0.126261	g_q05a_Never
41	0.0901094	vet_True
42	-0.182817	g_q08_Yes
43	0.129847	b_q10a_Yes
44	0.0124907	j_q04a_Yes
45	0.0453981	d_q14_Extremely dissatisfied
46	0.148551	d_q14_Extremely satisfied
47	0.112871	d_q14_Satisfied
48	-0.156307	g_q05g_Every day
49	0.0270132	g_q05g_Less than once a month
50	0.00192066	g_q05g_Never
51	0.12231	computerexperience_Yes
52	0.321902	f_q07b_Yes
53	-0.10849	g_q05d_Every day
54	-0.0590609	g_q05d_Less than once a week but at least once a month
55	0.0951881	g_q05d_Never
56	-0.161068	d_q06b_Stayed more or less the same
57	0.0578826	g_q06_Moderate
58	0.0576696	g_q06_Straightforward
59	-0.0708934	d_q12b_A lower level would be sufficient
60	-0.0614321	d_q12b_This level is necessary
61	0.368032	d_q06a_11 to 50 people
62	0.703443	d_q06a_251 to 1000 people
63	0.589748	d_q06a_51 to 250 people

	Coefficients	Feature
64	0.693836	d_q06a_More than 1000 people
65	-0.0191549	g_q05c_Every day
66	-0.161512	g_q05c_Less than once a month
67	0.0592944	g_q05c_Less than once a week but at least once a month
68	-0.0453372	g_q05c_Never
69	-0.00461924	f_q07a_Yes
70	-0.0420853	g_q05h_Every day
71	0.0849324	g_q05h_Less than once a month
72	-0.213333	g_q05h_Never
73	-0.402679	b_q10c_Not useful at all
74	-0.0579116	b_q10c_Somewhat useful
75	-0.0328139	b_q10c_Very useful
76	-0.0897247	d_q12c_1 to 6 months
77	0.00245779	d_q12c_3 years or more
78	-0.066277	d_q12c_7 to 11 months
79	-0.221253	d_q12c_Less than 1 month
80	-0.0371234	d_q12c_None
81	0.110397	g_q05f_Every day
82	-0.0965286	g_q05f_Less than once a month
83	0.00459112	g_q05f_Less than once a week but at least once a month
84	-0.0468762	g_q05f_Never
85	-0.0214164	g_q07_Yes
86	-0.0550972	edcat8_Post-secondary, non-tertiary (ISCED 4A-B-C)
87	-0.128319	edcat8_Primary or less (ISCED 1 or less)
88	-0.105555	edcat8_Tertiary - bachelor/master/research degree (ISCED 5A/6)
89	0.0686286	edcat8_Tertiary – bachelor degree (ISCED 5A)
90	-0.0615816	edcat8_Tertiary – master degree (ISCED 5A)
91	0.128934	edcat8_Tertiary – professional degree (ISCED 5B)
92	-0.655697	edcat8_Tertiary – research degree (ISCED 6)
93	0.0204709	edcat8_Upper secondary (ISCED 3A-B, C long)
94	0.193856	skill_1
95	0.123581	skill_2
96	0.254882	skill_3

Table: Lasso logistic regression for off-job training

	Coefficients	Feature
0	-0.0129761	age_r
1	0.00472379	j_q03b
2	0.0450784	yrsget
3	0.0114224	c_q09
4	0.00774523	c_q10a
5	0.080179	readytolearn
6	-4.92742e-08	earnmthallppp
7	0.133852	g_q05e_Every day
8	0.0622688	g_q05e_Less than once a month
9	0.0853484	g_q05e_Less than once a week but at least once a month
10	0.12126	g_q05e_Never
11	0.275416	edcat8_Post-secondary, non-tertiary (ISCED 4A-B-C)
12	-0.0969094	edcat8_Primary or less (ISCED 1 or less)
13	0.278165	edcat8_Tertiary – bachelor degree (ISCED 5A)
14	0.217442	edcat8_Tertiary – master degree (ISCED 5A)
15	0.107415	edcat8_Tertiary – professional degree (ISCED 5B)
16	-0.237701	edcat8_Tertiary – research degree (ISCED 6)
17	0.0375319	edcat8_Upper secondary (ISCED 3A-B, C long)
18	-0.0351465	gender_r_Male
19	-0.147956	g_q08_Yes
20	-0.0917169	j_q04a_Yes
21	0.0454495	g_q05a_Every day
22	-0.0569056	g_q05a_Less than once a month
23	0.0827699	g_q05a_Less than once a week but at least once a month
24	-0.0152595	g_q05a_Never
25	0.102236	g_q05f_Every day
26	-0.0766345	g_q05f_Less than once a week but at least once a month
27	-0.0269112	g_q05f_Never
28	0.447649	computerexperience_Yes
29	0.260128	f_q07b_Yes
30	0.0246258	b_q01b_Engineering, manufacturing and construction
31	-0.0336862	b_q01b_General programmes
32	0.222118	b_q01b_Health and welfare
33	-0.0330549	b_q01b_Humanities, languages and arts
34	0.0886899	b_q01b_Science, mathematics and computing

	Coefficients	Feature
35	0.0228378	b_q01b_Social sciences, business and law
36	0.127195	b_q01b_Teacher training and education science
37	0.156951	d_q09_A temporary employment agency contract
38	0.0109747	d_q09_An indefinite contract
39	-0.239307	d_q09_No contract
40	0.225348	d_q09_Other
41	0.790455	b_q10a_Yes
42	-0.290733	leaver1624_Not in education, did not complete ISCED 3, aged 16 to 24
43	-0.011474	d_q12c_1 to 6 months
44	-0.00826411	d_q12c_3 years or more
45	-0.114519	d_q12c_7 to 11 months
46	-0.233354	d_q12c_Less than 1 month
47	0.0759839	d_q12c_None
48	0.0204918	d_q13c_Every day
49	-0.106941	d_q13c_Less than once a month
50	-0.135916	d_q13c_Less than once a week but at least once a month
51	-0.328951	d_q13c_Never
52	0.638	g_q04_Yes
53	-0.106537	g_q05g_Every day
54	0.0573156	g_q05g_Less than once a month
55	0.0182027	g_q05g_Less than once a week but at least once a month
56	-0.0842075	g_q05g_Never
57	-0.101545	pared_At least one parent has attained tertiary
58	-0.0464013	pared_Neither parent has attained upper secondary
59	0.110924	d_q06a_11 to 50 people
60	0.278621	d_q06a_251 to 1000 people
61	0.220498	d_q06a_51 to 250 people
62	0.293571	d_q06a_More than 1000 people
63	0.155299	g_q07_Yes
64	0.0832232	g_q05d_Every day
65	-0.105838	g_q05d_Less than once a month
66	0.070324	g_q05d_Less than once a week but at least once a month
67	0.0703497	d_q06b_Increased
68	0.0796499	g_q05c_Every day
69	-0.098999	g_q05c_Less than once a month

	Coefficients	Feature
70	-0.0739767	g_q05c_Less than once a week but at least once a month
71	-0.22972	g_q05c_Never
72	-0.149715	d_q14_Extremely dissatisfied
73	0.0511862	d_q14_Extremely satisfied
74	-0.0127105	d_q14_Neither satisfied nor dissatisfied
75	0.00549697	vet_True
76	0.010915	g_q05h_Every day
77	0.00103673	g_q05h_Less than once a month
78	-0.0284805	g_q05h_Less than once a week but at least once a month
79	-0.372728	g_q05h_Never
80	-0.162708	d_q03_The private sector (for example a company)
81	0.0537657	g_q06_Moderate
82	-0.0106992	g_q06_Straightforward
83	-0.0561683	b_q10c_Not useful at all
84	0.404797	b_q10c_Somewhat useful
85	0.0754157	d_q04_t_Employee, supervising fewer than 5 people
86	0.105143	d_q04_t_Employee, supervising more than 5 people
87	-0.119443	d_q12b_A lower level would be sufficient
88	-0.170284	d_q12b_This level is necessary
89	0.114312	f_q07a_Yes
90	0.0914148	skill_1
91	0.000861359	skill_2

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