Journal of Statistics Applications & Probability
An International Journal

http://dx.doi.org/10.18576/jsap/130411

Multilevel Logistic Regression Analysis of Correlates of Graduate Employment by Fields of Specialization

Emmanuel Gabreyohannes

Department of Mathematics and Statistics, College of Finance, Management and Development, Ethiopian Civil Service University, Addis Ababa, Ethiopia

Received: 27 Aug. 2023, Revised: 29 Mar. 2024, Accepted: 03 Apr. 2024.
Published online: 1 Jul. 2024.

Abstract: A number of research settings involve data having a multilevel (hierarchical) structure. Failing to take into account such hierarchical structures may lead to wrong statistical inference. The objective of this study was to explore the correlates of employment status among graduates of Ethiopian Higher Education Institutions nested within their fields of specialization using hierarchical two-level logistic regression model. The study sample consisted of 2569 graduates nested within 20 fields of specialization. The impact of level-1 covariates and fields of specialization on employment outcome was explored using average marginal effects. The estimated variance of the random (field of specialization) effects was found to be significant – an indication that a multilevel model is appropriate. Likelihood ratio test confirmed that the multilevel random coefficients model was a better fit to the data. Besides demographic and socio-economic characteristics of graduates (and their households), the dimensions related to the skills and competences of graduates, namely perceived level of training of graduates on technical/practical skills and soft skills at their universities as well as cumulative grade point average, had significant influence on employment outcomes. The results also revealed that the effect of practical skills on graduate employment varied across fields of specialization. Average marginal effects analysis indicated that the probability of employment was lower for graduates who were unmarried, aged below 25, with disability, from a low income family and those graduates who perceived that their preparation for practical as well as soft skills required in the job market was less than expected/very poor. Moreover, practical and soft skills differentials in the probability of graduate employment were found to diminish with an increase in cumulative grade point average. To improve graduate employment, provision of adequate training in practical/technical and soft skills is recommended.

Keywords: average marginal effects, graduate employment, marginal effects at representative values, multilevel analysis, multilevel logistic regression model.

1. Introduction

In recent years, factors affecting graduate employment (one dimension of labor market outcomes) have been widely investigated (e.g., Demissie et al., 2021; Hossain et al., 2020; Fenta et al., 2019; Nauffal and Skulte-Ouaiss, 2018). In addition to knowledge, skills and competences of individual graduates as well as certain external or contextual factors (e.g., demographic & socio-economic determining factors), field of study (or specialization) has been widely recognized as one of the key factors that determine success in the job market. In other words, graduates' labor market outcomes may exhibit considerable variation depending on their fields of specialization (Giesecke and Schindler, 2008; Ballarino and Bratti, 2009; Biggeri et al. (2001)).

Consideration of field of specialization in analysis of employment outcomes results in data with a multilevel structure, that is, university graduates nested within fields of specialization. Graduates from the same cluster (field of study) may experience similar labour market outcomes than those from different clusters. In other words, observations within the same cluster may be correlated with one another which invalidate the classical assumption of independence between observations. In such cases, the traditional statistical methods which do not take into account the nesting structure of the data may not be appropriate. First, the variance of the estimated coefficients will be underestimated which put into question any statistical inferences drawn. Second, models that do not take into account the homogeneity of outcomes within clusters may also result in inconsistent parameter estimates if the response and the explanatory variables are related through a nonlinear model structure (Rodriguez and Goldman, 1995; Snijders and Bosker, 2012).

*Corresponding author e-mail: *emmanuel.gabreyohannes@ecsu.edu.et*

Multilevel regression models (also known as mixed-effects or hierarchical models) are best suited to properly analyze multilevel data. Such models overcome the drawbacks from conventional regression analysis by considering the nesting structure of the data into account. They incorporate fixed effects (like standard regression models) as well as random effects. The random effects capture the variation between higher level units that is not explained by the fixed effects. By incorporating cluster-specific random parameters, multilevel models split the total variance in the outcome into two: between-cluster variation and within-cluster (individual-level) variation that remains. This makes it possible to simultaneously estimate the effect of individual as well as cluster characteristics on the response variable. Multi (cluster) - level analysis will be more appropriate than the fixed effects approach if the share of between-cluster variation from the total outcome variance is higher (Rodriguez and Goldman, 1995; Goldstein et al., 2002; McCulloch and Searle, 2008).

In order to capture the variation in the response variable across higher-level units (e.g., variation in graduate employment across fields of specialization), one might be tempted to include these clusters as fixed effects using a set of indicator variables in a simple (single-level) logit model (together with background characteristics of subjects). One of the problems with this approach is that the estimates of the within-cluster effects will not be consistent unless the total sample size is large (Rabe-Hesketh and Skrondal, 2012). The other drawback is that introducing dummy variables for each of the individual fields of specialization is an inefficient and non-parsimonious strategy. In contrast, multilevel regression analysis captures the variation across the entire population of fields of specialization through a single random parameter (principle of parsimony). Moreover, an individual level association (e.g., the association between a graduate's CGPA and his/her employment status) in conventional regression analysis is assumed to be of the same magnitude in all level-2 units (fields of specialization). However, this assumption is too restrictive since there is a possibility that such associations may vary across level-2 units (Goldstein et al., 2002).

A number of studies incorporated field of specialization for predicting individual labor market outcomes through a fixed effects approach whereby the individual fields are introduced as dummy variables (e.g., Giesecke and Schindler, 2008; Ballarino and Bratti, 2009). The limitations associated with this approach are briefly discussed above. In fact, the study by Biggeri et al. (2001) applied a three-level discrete time survival model, but the analysis was primarily aimed at exploring the time to obtain the first job for graduates in Italian universities. To our knowledge, no studies in a developing country context have treated the fields of specialization as random effects and undertaken simultaneous estimation of measures of association at the cluster (field of study) level and at the individual graduate level in a multilevel framework. In this study, the employment status of graduates of Ethiopian HEIs was assessed in a multilevel framework using hierarchical two-level logistic regression model focusing on two main supply-side dimensions: the dimension relating to the body of knowledge, skills and competences of graduates, and that related to demographic & socio-economic factors.

The rest of the paper is structured as follows: Section two discusses the source of data, the response and explanatory variables, and statistical models for the analysis of multilevel data with binary outcomes. The results of the study and discussion are presented in Section three. The last section is devoted to conclusions and recommendations.

2. Materials and Methods

2.1 Source and structure of data

We used data from ‘A Survey on Alumni of Ethiopian Higher Education Institutions’ which was conducted in 2015 and contained data on several characteristics of university/college graduates (and their families) between 2010 and 2014 in Ethiopia. In this survey, primary data were gathered from graduates of First, Second and Third Generation public universities as well as private universities that have at least one graduated batch over the stated period. The sampling frame (including graduates’ field of study and contact addresses) was obtained from the Registrar’s Offices of the universities approached. The data were collected through mixed methods. Enumerators were dispatched to Addis Ababa, Mekelle, Bahir Dar, Gondar, Adama, Ambo, Dire Dawa, Harari and Hawassa, and gathered pertinent information using personal interviews. Additionally, data were gathered through telephone interviews and via e-mail (though the latter was not as such successful).

The survey data set has a multilevel structure, with graduates nested within fields of specialization. Fields of study with small number of graduates were discarded, and the final study sample consisted of 2569 graduates within 20 fields of specialization. The number of graduates per field of specialization ranged from 49 to 400, with a mean of 128.4.

2.2 Variables of the study

In this study, the response variable is whether a graduate is employed (full-time, part-time, self-employed) or not at the time of the survey. It is a dichotomous (binary) random variable which assumes the value 1 if a graduate was employed at the time of the survey, and zero otherwise. Graduate/household-level demographic & socio-economic factors selected for this study are gender, age, marital status, disability status, household monthly income and level of education of the household head. The set of competences explored include cumulative grade point average (CGPA), graduates' perceived level of subject matter (theoretical) knowledge and technical/practical skills acquired from their respective universities as well as their perceived level of training on soft skills that enhance their opportunities to find a job. Here CGPA is a continuous variable while the others are all categorical.

2.3 Statistical models for the analysis of multilevel data with binary outcomes

Multi-level (or mixed) effects models are the preferred models in situations where there is more than one source of random variability in the data. For instance, in addition to variability among individual graduates, there may also be random variability across the fields of specialization of those graduates, that is, graduates from certain fields may have a greater probability of employment compared to those from other fields (even after accounting for cluster level observable characteristics of graduates). Such variation can be captured by introducing cluster-specific random effects into the model. One possibility would be through random intercepts which allows the outcome to be higher (or lower) in some higher-level units (fields of specialization) than others. However, this approach is too restrictive in the sense that it does not allow the fixed effects to vary across clusters. Thus, a more general approach is introducing random coefficients so that we can account for cluster-to-cluster variability in the effect of explanatory variables on the outcome of interest (Snijders and Bosker, 2012; Breslow and Clayton, 1993).

Consider a two-level structure where a total of n level-1 units (individuals) are nested within J level-2 units (clusters). Let y_{ij} be the value of the dichotomous outcome variable associated with ith level-1 unit nested within jth level-2 unit, $j = 1, 2, \cdots, J$; $i = 1, 2, \cdots, n_j$.

2.3.1 Multilevel random intercept logistic regression model

In a random intercept regression model, introduce cluster-specific random effects so that the intercepts can vary randomly across clusters (in our case, across fields of specialization). A multilevel random intercept logit model is defined as:

$$\eta_{ij} = \log\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = x'_{ij}\beta + u_j \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where $\pi_{ij} = E(y_{ij} \mid x_{ij}, u_j) = \Pr(y_{ij} = 1)$, $x_{ij} = (x_{1j}, x_{2j}, \cdots, x_{pj})'$ is the $(p \times 1)$ covariate vector (with $x_{1j} = 1$ for the intercept), $\beta = (\beta_1, \beta_2, \cdots, \beta_p)'$ is the $(p \times 1)$ vector of unknown regression parameters, and u_j is the random cluster effect (or level-2 residual). The random intercepts $u_j \sim N(0, \sigma_u^2)$ are assumed to be independent and identically distributed across subjects in cluster j and independent of the covariates x_{ij}.

The intercept β_1 is interpreted as the log-odds that $y_{ij} = 1$ when $x_{ij} = 0$ and $u_j = 0$ (i.e., when the cluster-specific random effects are 'switched off'). On the other hand, β_k, $k = 2, 3, \cdots, p$, measures the effect of a 1-unit change in x_k (x continuous) on the log odds that $y_{ij} = 1$ after adjusting for the group effect u_j and the remaining predictor variables. Here we are looking at the effect of predictors for individuals within the same level-2 unit since the u_j are held constant (cluster-specific effect).

A special case of a random intercept model is the null or empty two-level logit model which contains only an intercept and group (level-2) effects with no explanatory variables:

$$\eta_{ij} = \log\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = \beta_1 + u_j \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

The intercept β_1 is shared by all subjects while the random effect u_j is specific to group j, $j = 1, 2, \cdots, J$.

2.3.2 Multilevel random coefficients logistic regression model

The multilevel model considered above successfully captures the variation in the probability of the outcome from one level-2 unit to another through the group-level random term u_j. However, it does not allow the effect of the explanatory variables to vary across clusters since the random effect was assumed to influence only the intercept of the model. The model can easily be extended to include multiple random effects. For this, let z_{ij} denote the $(r \times 1)$ vector of random-effect variables. The vector of random effects u_j is assumed to follow a multivariate normal distribution with zero mean vector and variance-covariance matrix $\Omega_u = E(u_j u_j')$. The model is now written as:

$$\eta_{ij} = \log\left[\frac{\pi_{ij}}{1-\pi_{ij}}\right] = x_{ij}'\beta + z_{ij}'u_j \quad \text{……………………….…. (3)}$$

The significance of the random slope variances is an indication that the effect of lower-level explanatory variables on the probability of the outcome does vary from one cluster to another (Snijders and Bosker, 2012).

2.4 The variance partition coefficient

The proportion of total variation in the response variable that is induced by between-cluster variation is measured by the variance partition coefficient (VPC). Given a continuous outcome, the VPC is defined as: $VPC = \sigma_u^2 / (\sigma_u^2 + \sigma_\varepsilon^2)$, where σ_ε^2 and σ_u^2 denote the between-subject variation (level-1 residual variance) and between-cluster variation (level-2 residual variance), respectively. In a multilevel regression model for binary outcomes, however, a direct estimate of σ_ε^2 is not available. The latent regression approach is often used for computing the VPC for such models. Consider a latent continuous variable y^* that represents an observed binary response y such that:

$$y_{ij} = \begin{cases} 1 & \text{if } y_{ij}^* > 0 \\ 0 & \text{if } y_{ij}^* \le 0 \end{cases} \quad \text{…………………….………….. (4)}$$

The multilevel regression model is written in terms of this continuous latent variable as:

$$y_{ij}^* = x_{ij}'\beta + u_j + \varepsilon_{ij} \quad \text{……………………..………. (5)}$$

In this latent regression model, the error (or level-1) variance is fixed and not estimated, that is, the errors ε_{ij} are assumed to follow a standard logistic distribution with mean zero and variance $\sigma_\varepsilon^2 = \pi^2/3$. Thus, an estimator of the VPC is given by $VPC = \sigma_u^2 / (\sigma_u^2 + \pi^2/3)$ when using a logit link (Goldstein et al., 2002; Li et al., 2008).

2.5 Marginal effects analysis

Most studies that utilize the logistic regression model focus on interpreting the coefficients of the fitted model in terms of odds ratios. One of the problems with odds ratios is that they are sensitive to omitted variables even if those omitted variables are not correlated with the independent variables already included in the model. Moreover, the odds ratio for a particular explanatory variable in multi-level logistic regression models is meaningful only on the condition that we are in the same level-2 unit (cluster) and the remaining explanatory variables are held constant (ceteris paribus). One possible solution is to express and interpret effects in the probability scale (instead of the log-odds scale). In this regard, average marginal effects (AME) are useful quantities of interest. In particular, they are preferred ways of interpreting the results from mixed-effects logistic regression models (i.e., when the model is not a case-control or fixed-effects model). To obtain the AME of a particular predictor variable in multi-level models, we hold this predictor at a constant, compute separate conditional probabilities for every cluster in the observed sample (using the actual observed values for all other explanatory variables) and then compute the average of these conditional probabilities. Thus, the effects have unconditional interpretations (Norton and Dowd, 2018; Mood, 2010).

One important issue that cannot be addressed through AMEs is the possibility that the effect of a given explanatory variable on the probability of an outcome may vary with the other characteristics of an individual. For example, the effect of family income on the probability of employment could be much greater for those graduates with low CGPA than those with higher CGPA. In order to assess such variation, marginal effects at representative values (MERs) are often used. MERs make it possible to explore the average change in the probability of an outcome for each of the explanatory variables at a particular combination (or range of values) of a predictor of interest (Williams, 2012).

2.6 Estimation of parameters

The maximum likelihood method is widely used to estimate the parameters of multilevel models when the outcome variable is continuous. Since there are no closed form solutions for the first order conditions for generalized linear mixed models, however, the true likelihood is approximated using numerical integration. Gauss–Hermite quadrature is often used to directly estimate the integral required to calculate the loglikelihood (Pan and Thompson, 2003). This method can be used to compare nested models through LR tests since the log likelihood itself is estimated. Alternatively, estimation based on adaptive Gauss-Hermite quadrature is a useful method among the likelihood-based procedures when a high degree of accuracy is desired. However, this method performs poorly for large datasets and in high dimensional spaces (McCulloch and Searle, 2008). In this study, Stata's maximum likelihood estimation procedure using adaptive quadrature is employed.

2.7 Assessing goodness of fit for multi-level generalized linear models

It is crucial to test the goodness of fit of a model before proceeding to make statistical inferences. Currently, well developed goodness of fit measures (tests) for generalized linear mixed effects models are in general not available. However, a number of studies found minimal relative bias in estimated regression coefficients and approximately correct model-based standard errors under model misspecification. Moreover, relative degree of robustness in estimation of the random effects variance under misspecification of the distributional shape of the random intercept was reported (e.g., Heagerty and Kurland, 2001; McCulloch and Neuhaus, 2011).

3. Results and discussion

3.1 Descriptive statistics

Data on a total of 2569 first-degree graduates were utilized for the present analysis. Table 1 presents the frequency and percentage distribution of graduate and household related characteristics disaggregated by employment status. The overall incidence of unemployment among graduates in the study period was found to be 29.9%.

Graduates who were below 25 years of age, unmarried, from families with low income, with disability and those who perceived that the subject matter knowledge, practical skill as well as soft skills acquired from their universities was less than expected or very poor appeared to be disadvantageous in landing on jobs in relative terms. On the other hand, there is no clear pattern regarding the influence of education of the household head on graduate employment. Moreover, we don't observe that much gender differential in graduate employment.

Table 1 Distribution of graduate and household related characteristics by employment status

Variable	Category	Employment status		
		Unemployed (Count (%))	**Employed** (Count (%))	**Total** (Count)
Gender	Female	230 (25.9)	657 (74.1)	887
	Male	538 (32.0)	1144 (68.0)	1682
Age	Below 25	309 (35.8)	555 (64.2)	864
	25-35	439 (28.1)	1126 (71.9)	1565
	36+	20 (14.3)	120 (85.7)	140
Marital status	Married	156 (19.8)	632 (80.2)	788
	Unmarried	612 (34.4)	1169 (65.6)	1781
Family income (ETB)	< 1000	284 (48.2)	305 (51.8)	589
	1000-2500	220 (37.0)	374 (63.0)	594
	2501-5000	185 (25.4)	543 (74.6)	728
	5001-10000	59 (11.3)	464 (88.7)	523
	More than 10000	20 (14.8)	115 (85.2)	135
HHH education	No education	226 (35.7)	407 (64.3)	633
	Elementary	118 (29.4)	283 (70.6)	401
	Secondary	126 (44.7)	156 (55.3)	282
	Certificate	76 (52.1)	70 (47.9)	146
	Diploma and higher	222 (20.1)	885 (79.9)	1107
Disability	Not disabled	724 (29.3)	1744 (70.7)	2468
	Disabled	44 (43.6)	57 (56.4)	101
Subject matter knowledge	Very well	327 (26.9)	888 (73.1)	1215
	Adequate	320 (29.9)	751 (70.1)	1071

	Less than exp./V.	121 (42.8)	162 (57.2)	283
Practical skill	Very well	186 (22.2)	650 (77.8)	836
	Adequate	268 (26.0)	762 (74.0)	1030
	Less than exp./V.	314 (44.7)	389 (55.3)	703
Soft skill	Very well	130 (17.4)	618 (82.6)	748
	Adequate	216 (23.3)	710 (76.7)	926
	Less than exp./V.	422 (47.2)	473 (52.8)	895
Employment status		768 (29.9)	1801 (70.1)	2569

3.2 Random intercepts model

We first estimate a model with subject-wise random effects but no fixed effects (i.e., no graduate characteristics). The results are given in Table 2. The estimated variance of the random effects is $\hat{\sigma}^2_{u_0} = 0.612$. The likelihood ratio statistic for testing the null hypothesis $H_0 : \sigma^2_{u_0} = 0$ was found to be significant (Chi-square = 272.51, p-value ≤ 0.001). Thus, there is a significant variation in the log-odds of getting employed from one cluster (field of specialization) to another. This result suggests that a multilevel model is appropriate. The fixed intercept $\hat{\beta}_0 = 0.744$ is interpreted as the overall log-odds of landing on a job for a typical graduate belonging to an 'average' field of specialization (i.e., a field with $u_{0_j} = 0$). Thus, graduates have $\exp(0.744)/(1+\exp(0.744)) = 68\%$ chance of getting employment across all fields of specialization, on average. Since the model is intrinsically nonlinear, the average of the field-specific probabilities of employment is in general different from the predicted probability of employment at an average field of specialization.

Table 2 Results of the fitted empty model

employstatus	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
_cons	0.7443382	0.1826271	4.08	≤0.001	0.3863957	1.102281

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
Field: Identity				
var(_cons)	0.612083	0.2120163	0.3104323	1.206851

LR test vs. logistic model: chibar2(01) = 272.51 Prob >= chibar2 ≤0.001

Figure 1 is a plot of the predicted random intercepts together with the 95% confidence intervals for the fields of specialization under study (so-called caterpillar plot). The plot can be used to examine field of specialization effects on graduate employment. The 95% confidence intervals for Management & Public Administration, Accounting, Business, Education, Computer Science & Information Systems, Health (Medicine, Nursing & Health Officer), and Economics lie above the horizontal line at zero, indicating that graduate employment in these fields of specialization is significantly above average. On the other hand, graduate employment is well below average for Agriculture & Animal Science, Geography, Statistics, Psychology & Sociology, History, Language (including journalism & communication) and Engineering. A number of studies also reported field of study differentials in graduate employment (e.g., Dayaratna-Banda and Dharmadasa, 2022; Wobse et al., 2022; Giesecke and Schindler, 2008; Ballarino and Bratti, 2009; Biggeri et al., 2001). However, field-wise comparison and contrast with our results may not provide useful insights since local labour market conditions and national contexts are more likely to vary across nations.

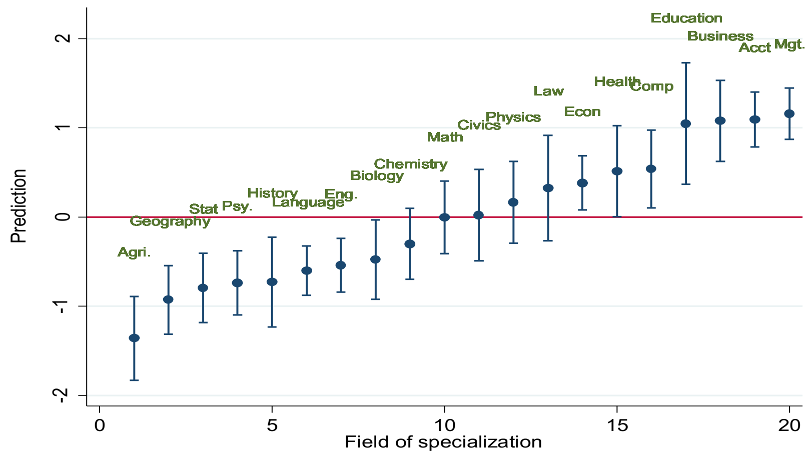

Fig. 1 Predicted random intercepts across fields of specialization

Next we fit a model by allowing the probability of employment to depend on the field of specialization as well as individual (and household level) characteristics of graduates. The results are presented in Table A1 (annex). The likelihood ratio test of the random intercepts logit model with predictor variables versus the empty model indicated that the former was a better fit to the data (Chi-square = 447.12, p-value ≤ 0.001). The results also revealed that the individual-level variance has decreased from 0.612 to 0.452 after the addition of background characteristics of graduates (and their households). The variance partition coefficient (or residual intra-class correlation) was found to be 0.121. Thus, adjusting for the effects of background characteristics of graduates, about 12.1% of the remaining variance in the propensity to land on a job is due to between-fields of specialization variation, while the balance (87.9%) is due to unobserved differences between graduates.

3.3 Random coefficients model

In a random intercepts model, we have assumed that the effects of individual characteristics on graduate employment are the same for each field of specialization (that is, the coefficients of all explanatory variables are fixed across fields). We now extend the model by allowing both the intercepts and the slopes of explanatory variables to vary randomly across fields of specialization. Each of the graduate/household level covariates was allowed to vary across clusters one at a time, and the LR test (which tests the null hypothesis that the variance components are all zero) was used to compare the random intercepts and the random coefficients models. The results revealed that the LR statistic for a random slope for practical/technical skills (which is dichotomized in the random slope part as 0 = less than expected/very poor, 1 = very well/adequate) was significant (Chi-square = 8.30, p-value = 0.0158). We therefore conclude that the effect of practical/technical skills does indeed differ across fields, and we need to take such variation into account.

Among the predictor variables (graduate characteristics) included in the model, eight of them were found to be significantly associated with the odds of employment. The two insignificant variables were gender and perceived level of subject matter (theoretical) knowledge acquired from the university. From the descriptive statistics in Table 1 we can see that 84.2% of the unemployed and 91.0% of the employed graduates perceived that they were very well or adequately prepared for the subject matter knowledge base required in the job market. Thus, the insignificance of this covariate might be attributed to the existence of little variation in the responses among employed and unemployed graduates. As for gender, our results are similar to those of Demissie et al. (2021) and Wobse et al. (2022) who found no gender differential in employment status among graduates in Ethiopia. However, the vast majority of studies found a significant gender effect in favour of male graduates (e.g., Ismail, 2011; Tamiru, 2017; Ayaneh et al., 2020).

The output from the random part of the model is shown in Table 3 below. We can obtain an expression for the between-fields of specialization variance as a function of practical/technical skills (x_{ij}), controlling for the remaining characteristics of graduates, as:

$$\text{var}(u_{0j} + x_{ij}u_{1j}) = \text{var}(u_{0j}) + x_{ij}^2\,\text{var}(u_{1j}) + 2x_{ij}\,\text{cov}(u_{0j}, u_{1j}) = 0.6436051 + x_{ij}^2(0.225203) + 2x_{ij}(-0.214529)$$

For practical/technical skill = 0 (less than expected/very poor), the between-field variance is given by:

$$\text{var}(u_{0j} + x_{ij}u_{1j} \mid x_{ij} = 0) = 0.6436051 + (0^2)(0.225203) + 2(0)(-0.214529) = 0.64361$$

The between-fields variance for practical/technical skill = 1 (very well/adequate) is computed as:

$$\mathrm{var}(u_{0j} + x_{ij}u_{1j} \mid x_{ij} = 1) = 0.6436051 + (1^2)(0.225203) + 2(1)(-0.214529) = 0.43975$$

By comparing the two estimated between-fields variances, we can see that between-field differences in graduate employment are greater for those graduates who claimed that their training at their university for practical/technical skills required in the job market was less than expected/very poor. In other words, field of specialization has the strongest effect on the probability of employment for graduates who felt that their training for practical/technical skills was not adequate or very poor.

Table 3 Estimated random effects parameters from the random coefficients model

Random-effects Parameters	**Estimate**	**Std. Err.**	**[95% Conf. Interval]**	
Field: Unstructured				
var(practi~C)	0.2252030	0.1379991	0.0677607	0.7484632
var(_cons)	0.6436051	0.2682786	0.2843197	1.4569070
cov(practi~C, _cons)	-0.2145290	0.1647589	-0.5374506	0.1083925

Figure 2 is a plot of field-wise slopes versus intercepts for practical/technical skills, controlling for other graduate characteristics. This plot may be used to identify fields of specialization that had low rate of employment (large negative intercepts) and steep gradients (strong positive relationship between getting employed and the level of training in practical/technical skills). These are the fields in the top left hand quadrant: Geography, Psychology & Sociology, Engineering and (to some extent) Agriculture & Animal Science. In order to improve graduate employment, provision of adequate training in practical/technical skills that are required in the job market may be targeted towards these fields.

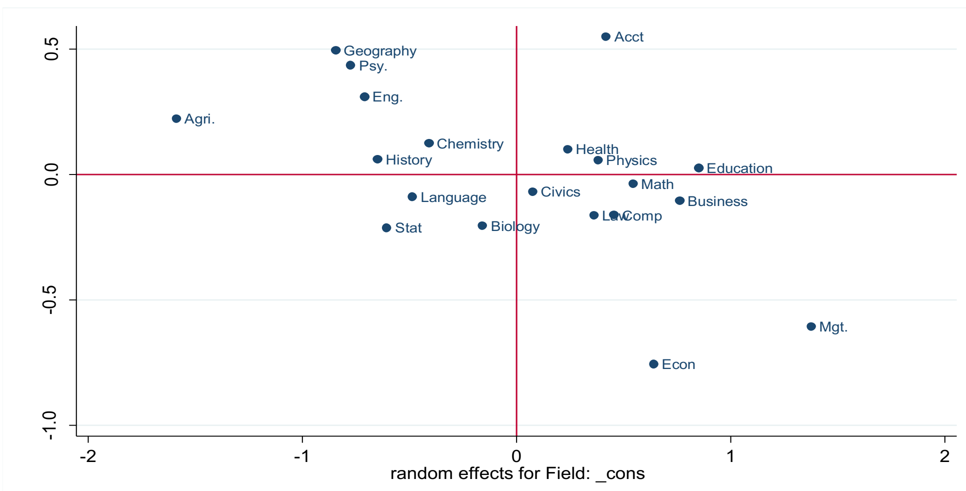

Fig.2 Plot of field-wise intercepts versus slopes for practical/technical skills

3.4 Average marginal effects (AME)

As discussed earlier, marginal effects are more informative than odds ratios since they express effects in the probability scale. Moreover, the AMEs in multi-level models are the estimated differences after all other variables in the model as well as group membership have been controlled for (that is, the figures are not conditional probabilities). In this section we explore the impact of covariates on the outcome using marginal effects.

The AMEs from the fitted multilevel logit model are given in Table 4. The results indicate that the probability of employment for an 'average' (or 'typical') graduate with disability was 9.43 percentage points lower as compared to that with no disability. Contrary to our result, Jackson (2014) found no evidence of a disability effect in graduates' job attainment in Australia. However, much of the literature reported disability as a barrier that hinders job attainment (e.g., Portillo-Navarro et al., 2022). One possible explanation is that the nature of the jobs available in the labour market may not allow the disabled to work in the context of underdeveloped economies. Moreover, the industry may refrain from recruiting disabled graduates for the avoidance of any sort of perceived risk associated with disability.

Surprisingly, the probabilities of employment for graduates from a household head with secondary, certificate and diploma & higher education were 18.93, 30.0 and 8.93 percentage points lower than those whose head had no education, respectively, on average. This result is inconsistent with a number of studies that found a positive effect of parental education on graduates' chance of employment (e. g., Biggeri et al., 2001). From the survey data, 42.1% of graduate employees with uneducated head of household were found to earn less than 2500 Birr. Pair-wise test of equality of proportions revealed that this figure is significantly higher than the proportion of graduate employees who earn less than 2500 Birr and came from households whose head had secondary (22.0%), certificate (27.1%) and tertiary education (18.8%). Thus, it might be the case that graduates from parents with lower educational level have settled for unstable/low paid jobs as compared to those with more educated parents.

The probabilities of employment for 'typical' graduates from a family whose monthly income was Birr 1000-2500, Birr 2501-5000, Birr 5001-10000 and over Birr 10000 were 13.84, 22.42, 33.94 and 27.82 percentage points higher than those with family income less than Birr 1000, respectively. This may be attributed to the complementary effect of family resources in determining labour market outcomes, that is, better-off families have the opportunities to use monetary resources, family networks, etc. to expand and retain relationships with key people who have the potential to help their wards to get a job and boost up their career (Aakvik et al., 2010). High earning families may also promote their wards to go for self-employment by facilitating capital for their ventures.

The results also indicate that the probability of employment for graduates aged below 25 was 4.59 percentage points lower as compared to those between 25 and 35 years of age, on average. A study by Demissie et al. (2021) in Ethiopia also revealed a significant age effect with older graduates having a lower rate of unemployment. However, the literature is full of conflicting results on the impact of age (e.g., Ballarino and Bratti, 2009; Jackson, 2014). Moreover, the probability of employment for an 'average' (or 'typical') married graduate was 6.86 percentage points higher than that of unmarried graduate. This result concurred with that of Ciriaci (2014) who reported that being married may create the necessary drive to search for and find a job, especially for males given that they usually have the greater financial responsibility.

Table 4 Average marginal effects

	dy/dx	Std. Err.	z	P>z	[95% Conf.	Interval]
Gender (Ref.: Female)						
Male	0.004	0.019	0.210	0.837	-0.033	0.041
Age (Ref.: < 25)						
25-35	0.046	0.019	2.460	0.014	0.009	0.083
36+	0.065	0.048	1.350	0.176	-0.029	0.158
Marital status (Ref.: Unmarried)						
Married	0.069	0.020	3.360	≤0.001	0.029	0.109
Family income (Ref.: < 1000)						
1000-2500	0.138	0.029	4.850	≤0.001	0.082	0.194
2501-5000	0.224	0.029	7.610	≤0.001	0.166	0.282
5001-10000	0.339	0.033	10.200	≤0.001	0.274	0.405
More than 10000	0.278	0.046	6.090	≤0.001	0.189	0.368
HHH education (Ref.: No educ.)						
Elementary	-0.018	0.024	-0.750	0.450	-0.064	0.029
Secondary	-0.189	0.031	-6.090	≤0.001	-0.250	-0.128
Certificate	-0.300	0.041	-7.400	≤0.001	-0.379	-0.221
Diploma and higher	-0.089	0.024	-3.750	≤0.001	-0.136	-0.043
Disability (Ref.: Not disabled)						
Disabled	-0.094	0.045	-2.110	0.035	-0.182	-0.007
Knowledge (Ref.: Very well)						
Adequate	0.016	0.018	0.890	0.376	-0.020	0.052
Less than exp./V. poor	-0.020	0.028	-0.720	0.474	-0.075	0.035
Practical skill (Ref.: Very well)						
Adequate	-0.031	0.021	-1.440	0.150	-0.072	0.011
Less than exp./V. poor	-0.084	0.024	-3.540	≤0.001	-0.130	-0.038
Soft skill (Ref.: Very well)						
Adequate	-0.060	0.021	-2.850	0.004	-0.102	-0.019
Less than exp./V. poor	-0.238	0.024	-9.780	≤0.001	-0.286	-0.191

The other factors concern the perception of graduates on a set of competences and skills required to get a job. The probability of landing on a job was 8.39 percentage points lower for those graduates who claimed that their preparation for practical/technical skills required in the job market was less than expected/very poor as compared to those who felt that they were very well trained, on average. Moreover, the probability of getting employment was 23.84 percentage points lower for those graduates who felt that their training for the soft skills required in the job market was less than expected/very poor as compared to those who reported that they were very well trained. This figure was 6.05 percentage points for those graduates who claimed that the training they received was adequate. These findings are consistent with a number of studies that reported the importance of technical and soft skills in graduate employment and employability (e.g., Ismail, 2011; Ambepitiya, 2016; Nauffal and Skulte-Ouaiss, 2018; Aboagye and Puoza, 2021; Nusrat and Sultana, 2019; Hossain et al., 2020).

3.5 Marginal effects at representative values (MER)

One of the advantages of MER is that it helps us to investigate how the marginal effects of a predictor of interest differ across ranges of values for one or more explanatory variables included in the model. Here, we specifically consider the variation in the response variable for selected graduate/household level characteristics across ranges of values for cumulative grade point average (CGPA). The results are displayed in Figure 3.

a) We have seen in the previous section that the AME for disability was 9.43 percent. Estimation of the same for various levels of CGPA, however, revealed that the effect of disability on the outcome exhibits some level of variation. For instance, the probabilities of employment for disabled graduates with CGPA of 2.0, 3.0 and 3.8 were 10.97, 9.89 and 8.33 percentage points lower than those graduates with no disability and the same level of CGPA, respectively, on average. Thus, the effect of disability on graduate employment was relatively higher at lower levels of CGPA.

b) At CGPA of 2.0, the probability of landing on a job for a graduate aged below 25 was 5.17 percentage points lower than that aged 25-35, on average. This difference steadily decreased to 3.87 percentage points at CGPA of 3.6. This finding implies that graduates' CGPA reduces the effect of age on the chance of landing on a job.

c) The probabilities of employment for a 'typical' graduate from a family whose monthly income is Birr 1000-2500, Birr 2501-5000, Birr 5001-10000 and over Birr 10000 were 15.24, 25.10, 38.69 and 32.11 percentage points higher than those with family income less than Birr 1000, respectively, at CGPA of 2.2. Even though the respective figures declined to 13.22, 20.42, 28.87 and 24.99 percentage points at CGPA of 3.6, the differences are still substantial.

d) At CGPA of 2.0, the probabilities of getting employed for a graduate from a household head with secondary, certificate and diploma & above level of education were 21.68, 33.33 and 10.58 percentage points lower than those whose head has no education, respectively, on average. The respective figures declined to 15.79, 26.93 and 7.00 percentage points at CGPA of 3.8. Again, the marginal differences are still substantial for the former two.

e) The probability of employment for graduates who claimed that they were very well trained on practical/technical skills at the university was 9.66 percentage points higher than those who reported that such training was less than expected/very poor at CGPA of 2.0, on average. The difference steadily decreased to 7.14 percentage points at CGPA of 3.6.

f) At CGPA of 2.2, the probability of landing on a job for 'typical' graduates who claimed that they were very well trained on soft skills at their university was 7.32 and 27.85 percentage points higher than those who reported that such training was adequate and less than expected/very poor, respectively. Even though the respective figures declined to 3.95 and 18.29 percentage points at CGPA of 3.8, the marginal difference is still substantial for the latter group. We can also observe that the soft skills differentials in the probability of graduate employment diminished with an increase in CGPA.

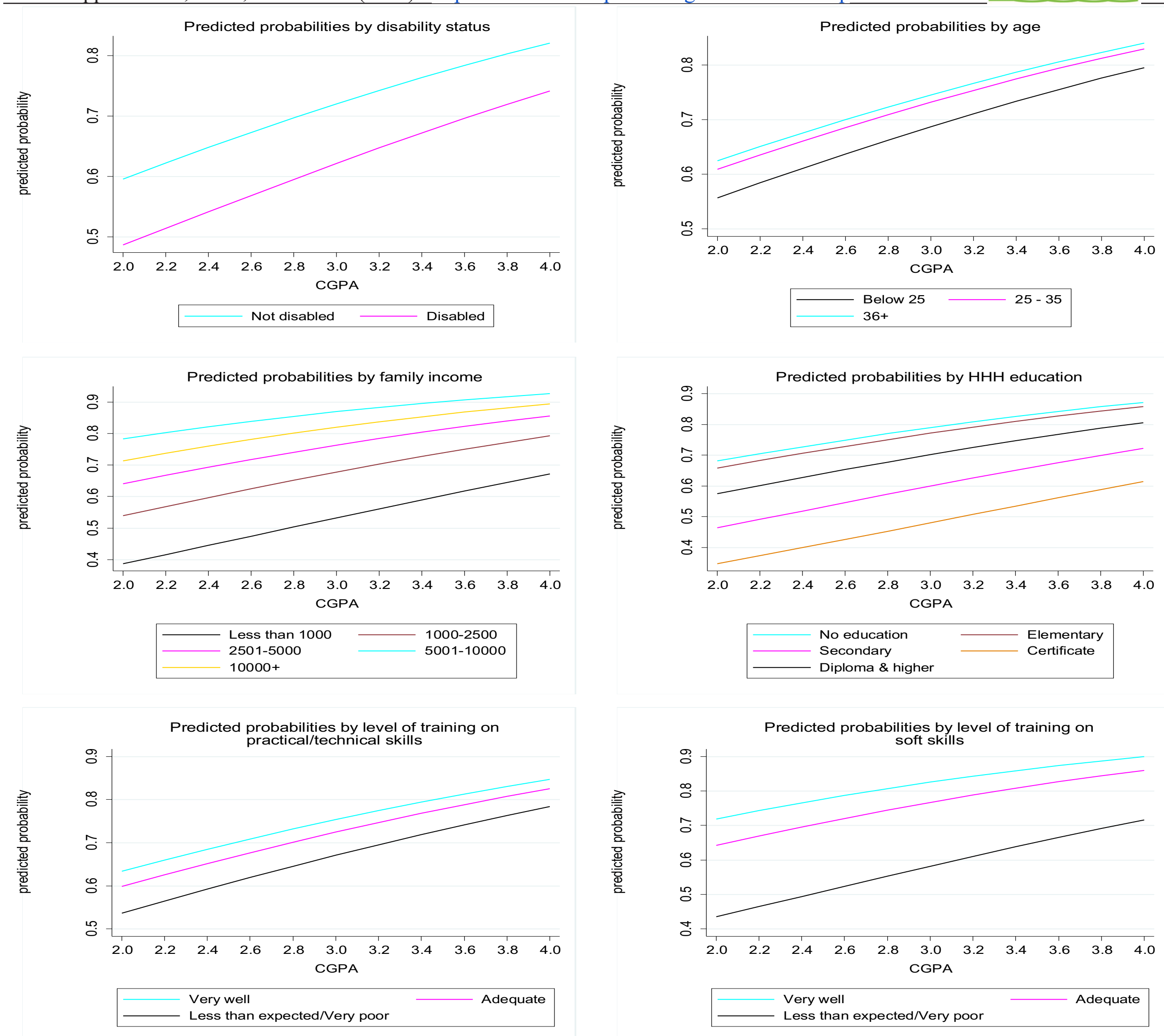

Fig.3 Marginal effects for range of values of CGPA

4. Conclusion

Multilevel regression models are the preferred models when data have a nested structure. They allow the estimation of the effects of cluster-level covariates (within-cluster variation) simultaneously with group effects (between-cluster variation). The main objective of this study was to identify and analyze correlates of employment of graduates of Ethiopian HEIs in a multilevel framework using hierarchical two-level logistic regression model, with graduates nested within fields of specialization. The analysis was mainly based on average marginal effects and marginal effects at representative values. The results revealed that there was significant variation in the log-odds of getting employed from one field of specialization to another, and thus, the use of multi-level models that consider such variation into account was justified.

Average marginal effects analysis indicated that the probability of employment was significantly lower for graduates who were unmarried, aged below 25, with disability, from a low income family and those graduates who perceived that their preparation for practical/technical as well as soft skills required in the job market was less than expected/very poor. From the fitted random coefficients model, we further found out that the effect of practical (technical) skills on graduate employment differed across fields of specialization. Specifically, graduates in Geography, Psychology & Sociology, Engineering and Agriculture & Animal Science were found to suffer most from lack of adequate training in practical skills that are required in the job market. Marginal effects at representative values also revealed that CGPA reduced the practical and soft skills differentials in the probability of graduate employment. The same was true for the effect of disability on graduate employment.

Based on the findings, the following key recommendations are forwarded:

- From the supply side, the results of the study revealed that the probability of getting employed was significantly lower for graduates who were ill-prepared in technical and soft skills. Thus, HEIs need to focus not only on hard (science) skills but also on practical and soft skills since the assurance of higher success outcomes in the job market depends on the level of harmonic integration between these skills.
- In this study, disability was found to have a significantly negative impact on graduates' employment after controlling for the effects of other graduate attributes and group membership. Therefore, concerned bodies should pay special attention to this segment of graduates by issuing and implementing appropriate regulatory mechanisms (such as affirmative actions).
- This study has also shown that there were variations in graduate employment across fields of specialization. Hence, students' placement should consider graduate employability as well as market demand.

Limitations

The study considered only supply side dimensions, and didn't control for labour market related (demand side) variables. Moreover, the analysis of graduates' level of preparation at their universities for subject matter (theoretical) knowledge as well as practical/technical and soft skills required in the job market was based on self-report data (possible inaccuracies in self-assessing levels of learning and development).

List of Abbreviations: AME – average marginal effects; CGPA – cumulative grade point average; HEI – higher education institutions; LR – likelihood ratio; MER – marginal effects at representative values; VPC – variance partition coefficient

Acknowledgement

We would like to acknowledge the anonymous reviewer for the thoughtful comments and suggestions. The comments were all valuable and very helpful for revising and improving our paper.

Declarations

Funding

No funding was received to assist with the preparation of this manuscript.

Data Availability

The datasets analyzed during the current study are available from the corresponding author upon request.

References

[1] Aakvik, A., Salvanes, K.G. and Vaage, K. Measuring Heterogeneity in the Returns to Education Using an Education Reform. *European Economic Review*, 2010, 54, 483-500.
[2] Aboagye, B. and Puoza, J. Study on Employability of Mechanical Engineering Graduates from Sunyani Technical University of Ghana. *Journal of Teaching and Learning for Graduate Employability*, 2021, 12(2), 185-205.
[3] Ambepitiya, K. Employability of Graduates of Public and Private Management Education Institutes: A Case Study of Two Institutes in Sri Lanka. *OUSL Journal*, 2016, Vol. 11, 113-134.
[4] Ayaneh, M.G., Dessie, A.A. and Ayele, A.W. Survival Models for the Analysis of Waiting Time to First Employment of New Graduates: A Case of 2018 Debre Markos University Graduates, Northwest Ethiopia. *Education Research International*, Vol. 2020.
[5] Ballarino, G. and Bratti, M. Field of Study and University Graduates' Early Employment Outcomes in Italy during 1995–2004. *LABOUR*, 2009, 23(3), 421-457.
[6] Biggeri, L., Bini, M. and Grilli, L. The Transition from University to Work: a Multilevel Approach to the Analysis of the Time to Obtain the First Job. *Journal of the Royal Statistical Society*, 2001, 164(2), 293-305.
[7] Breslow, N.E. and Clayton, D.G. Approximate Inference in Generalized Linear Mixed Models. *Journal of the American Statistical Association*, 1993, 88(421), 9-25.
[8] Ciriaci, D. University Choice, Research Quality and Graduates' Employability: Evidence from Italian National Survey Data. *European Educational Research Journal*, 2014, 13(2), 199-219.

[9] Dayaratna-Banda, O.G. and Dharmadasa, P.D.C.S. An Economics Analysis of Employability and Unemployment of Humanities and Social Sciences Graduates in Sri Lanka. *South Asian Survey*, 2022, 29(2), 155- 180.

[10] Demissie, M.M., Herut, A.H., Yimer, B.M., Bareke, M.L., Agezew, B.H., Dedho, N.H. and Lebeta, M.F. Graduates' Unemployment and Associated Factors in Ethiopia: Analysis of Higher Education Graduates' Perspectives. *Education Research International*, Vol. 2021.

[11] Fenta, H., Asnakew, Z.S., Debele, P.K., Nigatu, S.T. and Muhaba, A.M. Analysis of Supply Side Factors Influencing Employability of New Graduates: A Tracer Study of Bahir Dar University Graduates. *Journal of Teaching and Learning for Graduate Employability*, 2019, 10(2), 67- 85.

[12] Giesecke, J. and Schindler, S. Field of Study and Flexible Work: A Comparison between Germany and the UK. *International Journal of Comparative Sociology*, 2008, 49(4-5), 283-304.

[13] Goldstein, H., Browne, W. and Rasbash, J. Partitioning Variation in Generalised Linear Multilevel Models. *Understanding Statistics*, 2002, 1, 223-232.

[14] Heagerty, P.J. and Kurland, B.F. Misspecified Maximum Likelihood Estimates and Generalized Linear Mixed Models. *Biometrika*, 2001, 88(4), 973-985.

[15] Hossain, M., Alam, M., Alamgir, M. and Salat, A. Factors Affecting Business Graduates' Employability – Empirical Evidence using Partial Least-squares (PLS). *Education + Training*, 2020, 62(3), 292-310.

[16] Ismail, N.A. Graduates' Characteristics and Unemployment: A Study among Malaysian Graduates. *International Journal of Business and Social Science*, 2011, 2(16), 94-102.

[17] Jackson, D. Factors Influencing Job Attainment in Recent Bachelor Graduates: Evidence from Australia. *Higher Education*, 2014, 68(1), 135- 153.

[18] Li, J., Gray, B.R. and Bates, D.M. An Empirical Study of Statistical Properties of Variance Partition Coefficients for Multi-Level Logistic Regression Models. *Communications in Statistics – Simulation and Computation*, 2008, 37, 2010-2026.

[19] McCulloch, C.E. and Neuhaus, J.M. Misspecifying the Shape of a Random Effects Distribution: Why Getting it Wrong May Not Matter. *Statistical Science*, 2011, 26(3), 388-402.

[20] McCulloch, C.E. and Searle, S.R. Generalized, Linear and Mixed Models. 2008. Second Edition. John Wiley & Sons, Canada.

[21] Mood, C. Logistic Regression: Why We Cannot Do What We Think We Can Do, and What We Can Do about It. *European Sociological Review*, 2010, 26(1), 67-82.

[22] Nauffal, D. and Skulte-Ouaiss, J. Quality Higher Education Drives Employability in the Middle East. *Education + Training*, 2018, 60(9), 1057-1069.

[23] Norton, E.C. and Dowd, B.E. Log Odds and the Interpretation of Logit Models. *Health Services Research*, 2018, 53(2), 859-878.

[24] Nusrat, M. and Sultana, N. Soft Skills for Sustainable Employment of Business Graduates of Bangladesh. *Higher Education, Skills and Work-Based Learning*, 2019, 9(3), 264-278.

[25] Pan, J. and Thompson, R. Gauss-Hermite Quadrature Approximation for Estimation in Generalized Linear Mixed Models. *Computational Statistics & Data Analysis*, 2003, 18, 57-78.

[26] Portillo-Navarro, M.J., Lagos-Rodríguez, G. and Meseguer-Santamaría, M.L. Employability of University Graduates with Disabilities in Spain. *International journal of environmental research and public health*, 2022, 19(3), 1463.

[27] Rabe-Hesketh, S. and Skrondal, A. Multilevel and Longitudinal Modeling Using Stata. 2012. Third Edition. Stata Press, Texas, USA.

[28] Rodriguez, G. and Goldman, N. An Assessment of Estimation Procedures for Multilevel Models with Binary Responses. *Journal of the Royal Statistical Society*, 1995, A158, 73-89.

[29] Snijders, T.A.B. and Bosker, R.J. Multilevel analysis: An Introduction to Basic and Advanced Multilevel Modeling. 2012. Second edition. Thousand Oaks: Sage Publications.

[30] Tamiru, J. Exploring Employment Status and Education-Job Match among Engineering Graduates in Ethiopia: Policy Implications. *International Journal of African Higher Education*, 2017, 4(1), 2-15.

[31] Williams, R. Using the Margins Command to Estimate and Interpret Adjusted Predictions and Marginal Effects. *The Stata Journal*, 2012, 12(2), 308-331.

[32] Wobse, B.A., Menuta, Y.H. and Liga, A.D. Modeling of Waiting Time to First Employment of Graduates at Wolkite University, Ethiopia: Application of Accelerated Failure Time Models. *Cogent Education*, 2022, 9(1).

Annex

Table A1 Random intercept mixed-effects logistic regression

	Coef.	St. Err.	t-value	p-value	Sig.
Gender (Female)	0.000	.	.	.	
Male	0.024	0.115	0.21	0.836	
Age (< 25)	0.000	.	.	.	
25-35	0.278	0.111	2.50	0.013	**
36+	0.397	0.304	1.31	0.192	
Marital status (Unmarried)	0.000	.	.	.	
Married	0.428	0.129	3.32	0.001	***
Family income (< 1000)	0.000	.	.	.	
1000-2500	0.724	0.151	4.81	0.000	***
2501-5000	1.227	0.161	7.62	0.000	***
5001-10000	2.080	0.211	9.84	0.000	***
More than 1000	1.589	0.298	5.33	0.000	***
HHH education (No education)	0.000	.	.	.	
Elementary	-0.124	0.164	-0.76	0.449	
Secondary	-1.153	0.187	-6.18	0.000	***
Certificate	-1.758	0.238	-7.39	0.000	***
Diploma and higher	-0.579	0.159	-3.64	0.000	***
Disability (Not disabled)	0.000	.	.	.	
Disabled	-0.550	0.250	-2.20	0.028	**
Knowledge (Very well)	0.000	.	.	.	
Adequate	0.101	0.114	0.88	0.377	
Less than exp./V. poor	-0.121	0.167	-0.72	0.470	
Practical skill (Very well)	0.000	.	.	.	
Adequate	-0.192	0.133	-1.44	0.151	
Less than exp./V. poor	-0.505	0.141	-3.59	0.000	***
Soft skill (Very well)	0.000	.	.	.	
Adequate	-0.407	0.143	-2.85	0.004	***
Less than exp./V. poor	-1.393	0.140	-9.94	0.000	***
CGPA	0.704	0.123	5.72	0.000	***
Constant	-0.931	0.416	-2.23	0.025	**

**** p<0.01, ** p<0.05, * p<0.1*

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
Field: Identity				
var(_cons)	0.452397	0.1664034	0.2200015	0.9302802

LR test vs. logistic model: chibar2(01) = 272.51 Prob >= chibar2 = 0.0000

Likelihood-ratio test	LR chi2(20) = 447.12
(Assumption: A nested in B)	Prob > chi2 = 0.0000

Residual intraclass correlation

Level	ICC	Std. Err.	[95% Conf. Interval]	
Field	0.1208886	0.0390905	0.0626808	0.2204378

Author Biography

Emmanuel Gabreyohannes is Associate Professor of Statistics/Econometrics at the Mathematics and Statistics Department, College of Finance, Management and Development, Ethiopian Civil Service University. He received his PhD in Technical Mathematics (Econometrics) from the Institute of Mathematical Methods in Economics, Research Unit: Econometrics & Systems Theory, Technical University of Vienna, Austria. He is currently serving as the editor of the Journal of the Ethiopian Statistical Association (JESA).