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Research Article

Survival Models for the Analysis of Waiting Time to First Employment of New Graduates: A Case of 2018 Debre Markos University Graduates, Northwest Ethiopia

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This study was carried out to predict the time spell to first employment and to determine the effects of related factors on the timing of first employment on new graduates from Debre Markos University using survival models. The study used the 2018 Debre Markos University graduate tracer survey data. Cox PH and parametric accelerated failure time models were used. The Akaike information criterion (AIC) was used to select the best parametric model that could explain the waiting time to first employment. The median waiting time to first employment of graduates was found to be 15 months, showing that 50% of graduates managed to find their first job 15 months after their graduation date. In a comparison among parametric survival models, the log-logistic parametric model was better in describing the timing of graduates to first employment. Covariates such as gender, cumulative grade point average (CGPA) earned from the university, age at graduation, residence, field of study preference of graduates, and college/faculty were found to be statistically significant (p value <0.05) predictors of the waiting time to first employment. The log-logistic parametric model fitted the waiting time to the first employment data well and could be taken as an alternative for the Cox PH model.

1. Introduction

Securing a job immediately after graduation is a challenge for first-degree graduates in Ethiopia [1]. A number of university graduates stay unemployed or underemployed for a longer period [2, 3]. The number of students graduating from universities has been increasing year by year due to the massification of students joining higher education and the rapid expansion of programs in higher education [4]. However, despite this expansion, graduate unemployment poses a challenge to the country [5]. The country's labor market can only absorb a limited number of graduates, thereby thousands of fresh graduates remain unemployed [2, 6].

Graduate unemployment or delayed employment is attributed to the lack of soft or nontechnical skills of graduates, poor entrepreneur skills [7–10], and shortage of finance to create their own jobs [6]. Besides, factors such as the reputation of higher education institutions, the capacity of higher education to provide consultancy service, mismatch of skills between graduates, and employers' demands affect graduate employment [11]. Moreover, individual factors, including discipline type, graduate's achievement, gender, residence, family background, and graduates' job hunting skills influence graduates employment [12–16].

Unemployment affects not only the unemployed person but also family members and society at large [17]. The social and political consequences of large unemployment, especially among educated youth, can be serious [18]. As a result, the issue of graduate unemployment is becoming a fundamental issue that draws the attention of scholars [17, 19].

Assessing the employment characteristics and the underlying factors that influence undergraduate students' successful transition into the labor market is critical. Nevertheless, the prevalence of unemployment and associated factors in Ethiopia is not well identified and documented despite the efforts made by some Ethiopian public universities, including Addis Ababa University [2], Debre Berhan University [20], and Bahir Dar University [21]. Besides, Batu [6] studied the determinants of youth unemployment in urban areas of Ethiopia, and Reda and Gebre-Eyesus [1] studied graduates and their implications for unemployment in Ethiopia. Cox [22] studied the supply side factors influencing the employability of new graduates.

Nevertheless, the aforementioned studies were either attributed to graduates in a specific field of study, which lacked inclusiveness or used inadequate statistical methods to explore the factors for graduate unemployment.

Thus, the purpose of this study was to determine the predictors related to graduates' waiting time to first employment of Debre Markos University, 2018 bachelor's degree graduates using survival models. In this study, the efficiency of two survival regression approaches, Cox regression, and parametric AFT were compared to find out the best model that describes the waiting time to first employment.

2. Methodology

2.1. Study Population and Data Collection Procedures. This study used 2018 graduate tracer survey data from Debre Markos University. In the 2018 academic year, 2716 students graduated from 35 undergraduate regular programs from Debre Markos University. A total of 1105 graduates were selected using the sampling technique suggested by Cochran [23].

The following steps were followed to collect data from 1105 graduates. In the first step, graduates were required to fill their baseline information such as their college/faculty, field of study, gender, age, cumulative grade point average (CGPA), parents' education level, region where graduates were originally from, original residence, and other related variables immediately after their graduation date. A questionnaire used for data collection was taken from the Ethiopian Ministry of Education prepared nationally for all Ethiopian universities to conduct tracer studies with slight modifications. In the second step, having spent over 16 months, graduates were contacted on their phone to report their current situation with respect to employment status and other related variables. To do so, sixteen data collectors were recruited and trained on the data collection procedure. The information obtained from the questionnaires and telephone interviews was entered into Excel sheets and subsequently transferred into *R* software for analysis.

2.2. Variables. The outcome variable was the time spent from the effective date of graduation to first employment of graduates (in months). Demographic and environment-related factors that are assumed as potential determinants of waiting time to employment of graduates to their first employment were used. Accordingly, gender (female or male), age at graduation in years, college/faculty (CANaRM, CHM, IOT, IEBS, NCS, and CBE), CGPA category, residence originally lived by graduates (urban or rural), educational qualification achieved by either mother or father (not educated, primary, or secondary school and above), if Debre Markos was graduates preference to study (yes or no), receiving training on job searching method training during their stay in the university (yes or no), and if a graduate studied his/her preferred fields of study (yes or no) were considered as covariates.

2.3. Statistical Analyses. The baseline characteristics of the study population were reported using descriptive statistics. The Kaplan–Meier method was used to estimate the unemployment curve. Survival regression models such as Cox PH and parametric AFT were applied to assess the association between independent variables and waiting time to first employment, upon examining different model assumptions.

2.3.1. Survival Data Analysis: The Basics. In essence, survival analysis is a statistical method for data analysis in which the outcome variable of interest is the time to the occurrence of an event [24]. According to Orbe et al. [25], the distribution of survival times is characterized by any of three functions: survival function, probability density function, or the hazard function.

Let T be a nonnegative random variable that describes the length of time until graduate employment. In our case, T would measure the duration of the first unemployment spell, which would start when the graduate starts his/her job search ($T = 0$) and would finish when the graduate finds his/her first job (event time, $T = t$). The survival function, denoted by $S(t) = P(T > t)$, is one of the basic quantities employed to describe time-to-event phenomena and is defined as the probability of an individual being event-free/unemployed beyond time t. The hazard function (or hazard rate) specifies the instantaneous rate of failure at $T = t$, conditional upon survival to time t, and is given by $h(t) = f(t)/S(t)$, where $f(t)$ is the probability density function. In this particular case, the hazard function represents the probability of finding a job at $T = t$, given that he/she has survived (has been unemployed) until t.

2.4. Nonparametric Methods. The Kaplan–Meier (KM) estimator, which was proposed by Kaplan and Meier [26], is one of the standard nonparametric estimators of the survival function (unemployment curve), $S(t)$. The KM estimator produces the waiting time to first employment curve directly from the data as follows:

Let rank-ordered waiting times to the first employment are given by $0 \leq t_{(1)} < t_{(2)} < \ldots < t_{(r)} \leq \infty$; then,

$$\widehat{S}(t) = \begin{cases} 1, & \text{if } t < t_{(1)}, \\ \prod_{j: t(j) \leq t} \left[1 - \frac{d_j}{r_j}\right], & \text{if } t \geq t_{(1)}, \end{cases} \quad (1)$$

where d_j is the observed number of employments at time $t_{(j)}$, and r_j is the number of graduates who are seeking jobs at time $t_{(j)}$.

2.5. Regression Models for Survival Data

2.5.1. Cox Regression Model. Cox regression (or proportional hazards regression), first developed by Cox in 1972, is a statistical method for investigating the effect of several variables on the time a specified event takes to happen [27]. A multivariable Cox proportional hazards model is given by the following equation:

$$\begin{aligned} h(t \mid \mathbf{Z_i}) &= h_0(t)\exp\left(\beta_1 z_1 + \beta_2 z_2 + \cdots + \beta_p z_p\right) \\ &= h_0(t)\exp(\mathbf{Z_i}\boldsymbol{\beta}), \end{aligned} \quad (2)$$

where $h(t \mid Z)$ is the hazard function, that is, the hazard at time t for an individual with a given specification of a set of explanatory variables, Z, which are assumed to be time-independent, and h_0 (t) is arbitrary, the unspecified non-negative function of time known as baseline hazard, which corresponds to the hazard when all predictor variables are equal to zero. $\mathbf{Z}$ is the vector of covariates, and β denotes the vector of the regression coefficients, which is estimated using the partial likelihood method. The term $\exp(\beta' \mathbf{Z})$ depends on the covariates, but not time.

The Cox regression model is a semiparametric model where it makes no assumptions about the form of the nonparametric part of the model, h_0 (t), but assumes a parametric form for the effect of the predictors on the hazard. The main assumption of the model is the proportionality of hazards in that the hazard function of one individual is proportional to the hazard function of the other individual. The Cox PH model states that the factors under study act multiplicatively on the baseline hazard function and either increase or decrease the baseline function at a constant rate [28]. To measure the model adequacy, Schoenfeld residuals, Cox-Snell residuals, and deviance residuals can be used.

2.6. Parametric Methods. Accelerated failure time (AFT) is an alternative to the proportional hazard (PH) model, which needs distributional assumptions [25, 29]. Under AFT models, we measure the direct effect of the explanatory variables on the survival time instead of the hazard, as we do in the PH model. This characteristic allows for an easier interpretation of the results because the parameters measure the effect of the correspondent covariate on the mean survival time [30]. The effects of the covariates in the following equation are either to accelerate or decelerate the event time by some constants [31].

$$\ln T = \boldsymbol{\mu} + \boldsymbol{\alpha}' \mathbf{z} + \boldsymbol{\delta\varepsilon}, \quad (3)$$

where $\boldsymbol{\alpha}' = (\alpha_1, \alpha_2, \ldots, \alpha_p)$ is a vector of regression coefficients, μ is the intercept, δ is a scale parameter, and ε is the error assumed to have a particular distribution. Common choices for the error distribution include the standard normal distribution, which yields a log-normal regression model, the extreme value distribution with one parameter, which yields an exponential regression model, the extreme value distribution with two parameters, which yields a Weibull regression model, log-gamma, which yields a gamma distribution, or a logistic distribution, which yields a log-logistic regression model.

2.7. Model Selection and Adequacy. Akaike's information criterion (AIC), introduced by Akaike in 1973 [32], was used to select a relatively efficient model.

$$\text{AIC} = -2\log(L) + 2(k + c + 1), \quad (4)$$

where L and K, respectively, are the likelihood value and the number of covariates of the model, and c is the number of model-specific distributional parameters, such that in the model, $c = 1$ for exponential and $c = 2$ for Weibull and log-normal models. The model with a smaller AIC fits the data better than the model with a large AIC value. It can be used to compare the adequacy of multiple, probably nonnested models. Assessing the PH assumption for all covariates in the Cox PH model should be an essential aspect of the modeling process when using the Cox PH model. Hence, the PH assumption of the model should be assessed to confirm if the ratio of hazard functions is the same at all time points. In this study, the scaled Schoenfeld residuals were analyzed to validate the proportional hazards assumption. *R* statistical software version 3.6 for Windows was employed to carry out the statistical analysis.

3. Result

3.1. Descriptive Statistics. At the end of the study period, 42.4% of the graduates were willing to be employed during the reference period but still unemployed. In addition, three (0.27%) graduates' waiting times were not specified. Furthermore, 4 (0.3%) graduates were employed even before they had completed their degrees.

Among the graduates stated in Table 1, 708 (64%) of them were male and the remaining 397 (36%) were female. Among the 397 female graduates who responded to their employment status, 204 (51.4%) secured their job, whereas from a total of 708 male graduates, 432 (61%) were employed, revealing that the percentage of unemployed female graduates was higher than that of male graduates. Moreover, there was a statistically significant gender difference regarding whether graduates are currently employed (chi-square = 6.5 and p value = 0.039). As for the graduates' distribution by their cumulative grade average, the majority (36.1%) of the graduates CGPA was between 2.75 and 3.24,

Table 1: Debre Markos University graduates' employment status by their characteristics and the p values for the log-rank test of equality of survivor functions.

Variables	Category	Employment status: Employed, mean (SD), n (%)	Employment status: Not employed, mean (SD), n (%)	p value
Age at graduation in years		23.90 (0.07)	23.77 (0.05)	
Gender	Female	204 (51.4)	193 (48.6)	<0.001
	Male	432 (61)	276 (39)	
College/faculty	CHSM	20 (10.1)	178 (89.9)	<0.001
	CANaRM	94 (44.3)	118 (55.7)	
	CBE	101 (43.9)	129 (56.1)	
	IEBS	36 (69.2)	16 (30.8)	
	Law	1 (2.6)	38 (97.4)	
	NCS	59 (49.6)	60 (50.4)	
	Technology	157 (61.6)	98 (38.4)	
CGPA category	2–2.74	125 (41.9)	173 (58.1)	<0.001
	2.75–3.24	202 (55.6)	161 (44.4)	
	3.25–3.74	206 (71.3)	83 (28.7)	
	3.75–4.00	46 (83.6)	9 (16.4)	
Region where the graduate is from	Addis Ababa	22 (61.1)	14 (38.9)	0.0002
	Amhara	504 (55.4)	405 (44.6)	
	Oromia	24 (64.9)	13 (35.1)	
	SNNPR	45 (86.5)	7 (13.5)	
	Tigray	16 (57.1)	12 (42.9)	
	Others	25 (58.1)	18 (41.9)	
Father education attainment	Not educated	321 (56.4)	248 (43.6)	0.16
	Primary school	166 (58.0)	120 (42.0)	
	Secondary school and above	90 (56.6)	69 (43.4)	
Mother education attainment	Not educated	402 (58.0)	291 (42)	0.64
	Primary school	133 (55.2)	108 (44.8)	
	Secondary school and above	70 (60.9)	45 (39.1)	
Residence where the graduate is originally from	Rural	260 (45.3)	314 (54.7)	<0.001
	Urban	377 (71.0)	154 (29.0)	
Field of study preference	Yes	364 (41.7)	508 (58.3)	0.03
	No	78 (51.3)	74 (48.7)	
Study location preference	Yes	318 (58.2)	228 (41.8)	0.79
	No	123 (58.6)	87 (41.4)	
Ever got consultancy services in the university	Yes	132 (52.4)	120 (47.6)	0.33
	No	458 (61.4)	288 (38.6)	

Mean with standard deviation (SD) is used to summarize continuous variables; frequency (n) with percentage (%) is used to summarize the categorical variables.

whereas 28.52% and 5.5% of the graduates attained CGPA 3.25–3.75 and 3.75–4.00, respectively. The remaining 29.7% graduates scored a cumulative grade point average between 2 and 2.74. The mean age of the respondents at graduation was 23.85 (SD = 1.6) years. The majority, 909 (82.3%), of the graduates were ordinally from the Amhara region, and the remaining (17.7%) were from the other 8 regions.

3.2. Explanatory Analysis Using Nonparametric Methods. Kaplan–Meier estimates were used to construct the survival function for the waiting time to first employment. From Figure 1, the median time to first employment of graduates was found to be 15 months, which indicates that 50% of the graduates managed to find their first job by 15 months after their graduation date, and the other 50% did not secure their first job. The probability of being unemployed declines sharply fifteen months after graduation.

To give a description of how graduates' unemployment waiting time to first employment was distributed by covariates, Kaplan–Meier curves were drawn for covariates such as gender, college, grade point average, and residence of graduates as presented in Figure 2. Accordingly, graduates' cumulative grade point average (CGPA) and region of the graduates showed considerable differences in terms of unemployment curves for each category of the covariates, revealing that these covariates show significant differences regarding employment of graduates. For the first fifteen months after graduation, the unemployment rate curve for males is continuously below the unemployment rate curves of female's, suggesting that male graduates had significantly better employment than their female counterparts during

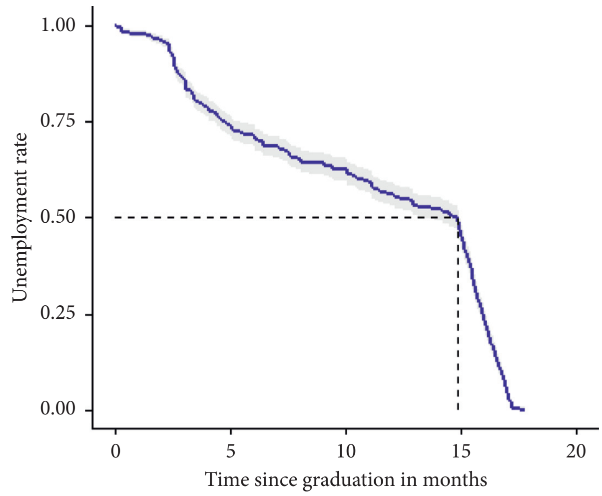

Figure 1: Kaplan–Meier curve for the waiting time until the first employment.

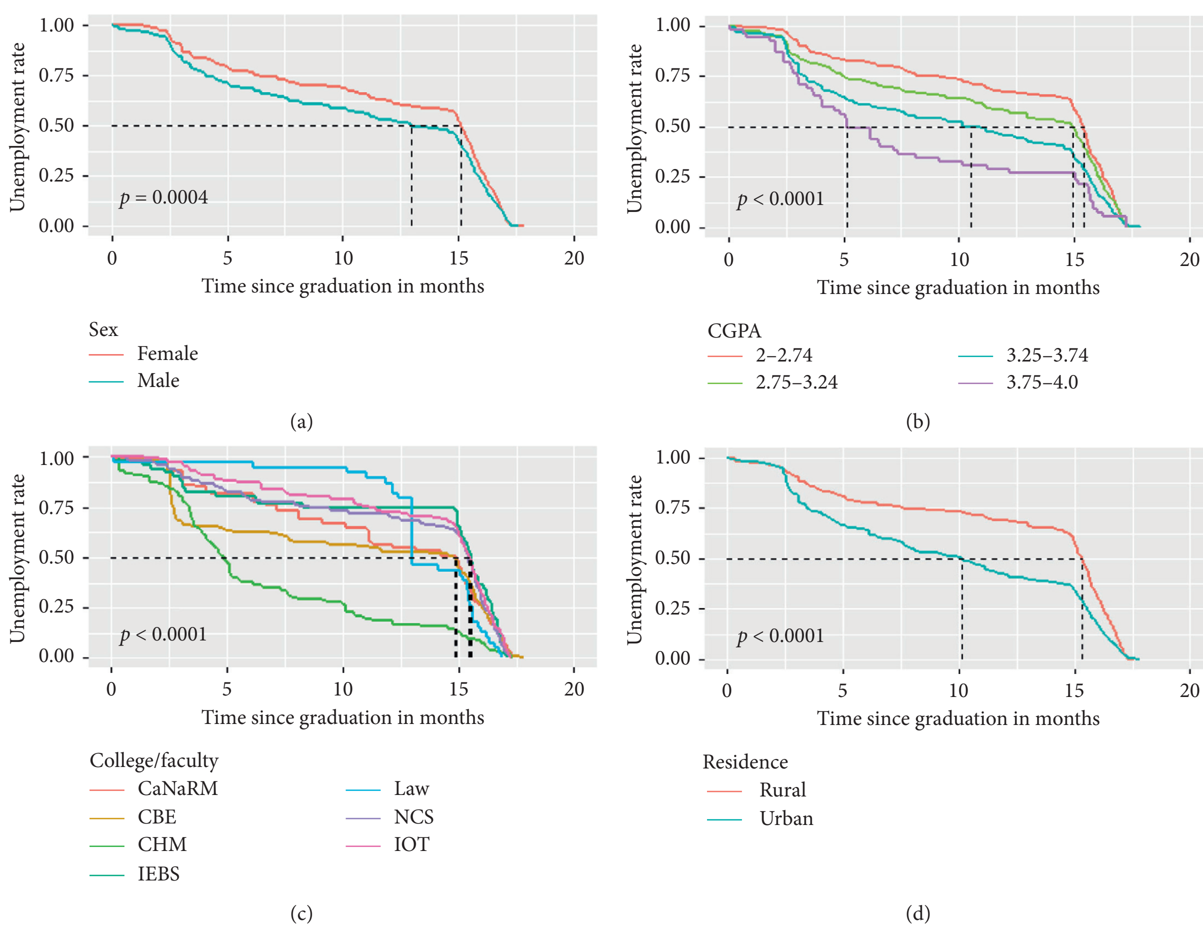

Figure 2: Kaplan–Meier curve for the waiting time for the first employment by gender, college, CGPA, region, and residence of graduates. CANaRM: College of Agriculture and Natural Resource Management, CHM: College of Health Science and Medicine, IOT: Institute of Technology, IEBS: Education and Behavioral Science, NCS: Natural and Computational Sciences College, and CBE: College of Business and Economics.

the first fifteen months. However, about sixteen months after graduation, the unemployment rate of females has decreased faster than that of males. Consequently, the differences between the two curves become almost nonexistent after 16 months after graduation. The unemployment curves of the graduates are considerably different for each college/faculty that the students graduate from. It is clear that from Figure 2(c) that graduates from the health science and medicine unemployment rate dropped faster than that of the graduates from the remaining colleges in the study, telling graduates from Health Science and Medicine found employment much faster than the other graduates from other colleges/faculty. The employment rate of law school graduates stayed constant up to 12 months after their graduation, although it sharply dropped after 12 months of their graduation. This is for the fact that the majority of law graduates were on inductive training before they were assigned for their first job by the government.

3.3. Cox Proportional Hazard Model Result. The first step considered in the model building procedure was to explore the relationship between each covariate and time to employment, univariately. Accordingly, in the univariate Cox proportional hazards regression analysis, age at graduation (p value <0.001), gender (p value <0.001), college/institute/school categorization of the graduates (p value <0.001), grade point average (p value <0.001), the region where the graduate were from (p value =0.02), place of residence (p value <0.001), and field of study preference (p value =0.02) show a statistically significant association with time to first employment at the 5% level of significance, However, parent's education levels (p value =0.2 each), ever receiving consultancy service about job hunting (p value =0.3245) and study area preference were found to have no significant association. The multivariable model containing all the significant covariates in the univariable analysis is described in Table 2.

3.4. PH Assumption Assessment and Overall Goodness-of-Fit. Incorporating variable(s) not satisfying the PH assumption leads to an inferior fit of a Cox model, that is, the power of test is reduced for both variables with constant and nonconstant HR in the model [33]. Table 3 reveals the p values of the tests based on the scaled Schoenfeld residuals for nonproportional hazard assessment generated by the cox.zph function survival package in *R* software. The results of the test support evidence of deviation from the proportionality assumption. This is because some of the p values for testing whether the correlation between Schoenfeld residual for these covariates and ranked survival time is less than 0.05.

As a result, accelerated failure time models with different distributional assumptions were built to model the waiting time to first employment.

3.5. Accelerated Failure Time Model Results. Parametric models such as Weibull, log-normal, log-logistic, and exponential models were carried out to identify a model that fits the data better. The summary of log-likelihood and AIC is presented in Table 4. Akaike's information criterion (AIC) statistic for the parametric and semiparametric survival models are 2191.555, 2194.743, 2188.247, and 2214.241 for Weibull, log-normal, log-logistic, and exponential models, respectively. The rule is that any model that conforms to the observed data should adequately lead to a smaller AIC. Hence, the log-logistic model appears to be with minimum AIC and BIC values among all other competing parametric models, revealing that it is the most efficient model to identify the predictors of the waiting time to first employment of the new graduates.

The result for log-logistic, which is a relatively efficient model, is presented in Table 2, with the estimated values of the coefficients, time ratio (TR) and its 95% CI, and p value. Although the proportional hazard assumption was violated, the results of the Cox PH model are also presented alongside for comparison purpose. The result of the log-logistic model is similar to that of the hazard models in detecting the significant predictors of time to first employment and their directional effects (positive or negative effect). However, the interpretations are not the same. Nevertheless, gender and field of study preference had a statistically significant association with the waiting time for the first employment based on the log-logistic model at 5% level of significance but not in the Cox PH model.

The estimate of shape parameter in the log-logistic with gamma was 0.63, which is less than unity, suggesting that the probability of getting a job decreases monotonically with time. After adjusting for other independent variables, age at graduation, gender, college/faculty, CGPA, and place of residence were associated with waiting time to first employment. A predictor with a positive coefficient (time ratio or acceleration factor greater than unity) implies that the variables prolong the waiting time to first employment. Accordingly, the acceleration factor for age was 0.86 (p value <0.001), indicating that older graduates had the tendency to have shorter waiting times until first employment. The median waiting time for males was 0.82 times lower than that of females. As for the CGPA earned from the university, it was found that compared to the interval of 3.74–4.0 CGPA receivers, graduates who earned CGPA in 3.24–3.75 range have to wait 1.31 times (p value = 0.09) and 2.75–3.24 graders have to wait 1.71 times (p value <0.001), while low achiever (2.0–2.74) graduates have to wait 2.32 times (p value <0.001) longer. When comparing graduates who were ordinally from urban areas to those who were from rural, those who were from rural areas had to wait 2.15 times (p value <0.001) longer to find their first job revealing that graduates from urban areas had shorter waiting time to first employment compared to those from rural areas.

Those graduates from all colleges had longer waiting times for first employment as compared to the college of health science and medicine. However, the difference in the waiting time of first employment between school of law and college of health science and medicine is not statistically significant (TR = 0.71, p value = 0.3). The results in Table 2 also show that the median waiting time until first employment for graduates who studied their preferred fields was 0.8 times (p value = 0.049) shorter than that of graduates who did not study their preferred fields.

Table 2: Analysis of associated factors of unemployment time based on Cox PH and log-logistical AFT models.

Variable	Cox PH model HR (95% CI)	p value	Log-logistic model TR (95% CI)	p value
Age	1.1 (1.07, 1.18)	<0.001	0.86 (0.82, 0.9)	<0.001
Gender (reference: female)				
Male	1.19 (0.96, 1.46)	0.12	0.82 (0.69, 0.98)	0.03
College/faculty (reference: medicine and health science)				
CANaRM	2.41 (1.91, 3.05)	<0.001	0.43 (0.33, 0.55	<0.001
CHM	1.96 (1.56, 2.46)	<0.001	0.48 (0.37, 0.61)	<0.001
IEBS	3.08 (1.98, 4.79)	<0.001	0.29 (0.17, 0.51)	<0.001
Law	1.85 (0.96, 3.58)	0.067	0.71 (0.37, 1.38)	0.3
NCS	1.99 (1.46, 2.71)	<0.001	0.48 (0.34, 0.69)	<0.001
Technology	4.59 (3.53, 5.96)	<0.001	0.19 (0.14, 0.27)	<0.001
Region (reference: Addis Ababa)				
Amhara	1.07 (0.66, 1.73)	0.80	1.13 (0.74, 1.74)	0.57
Oromia	1.03 (0.54, 1.96)	0.93	1.27 (0.72, 2.24)	0.41
SNNPR	1.35 (0.76, 2.41)	0.30	0.73 (0.43, 1.24)	0.24
Tigray	1.65 (0.81, 3.38)	0.17	0.78 (0.42, 1.46)	0.44
Others	1.09 (0.45, 2.64)	0.80	1.04 (0.48, 2.27)	0.92
CGPA category (reference: 3.75–4.00)				
2.00_2.74	0.41 (0.28, 0.60)	<0.001	2.32 (1.64, 3.28)	<0.001
2.75–3.24	0.57 (0.40, 0.80)	<0.001	1.71 (1.23, 2.38)	<0.001
3.25–3.74	0.75 (0.54, 1.04)	0.08	1.31 (0.95, 1.82)	0.09
Residence (reference: rural)				
Urban	2.15 (1.78, 2.58)	<0.001	0.5 (0.43, 0.59)	<0.001
Graduate studied his/her preferred fields of study				
Yes	1.25 (0.96, 1.64)	0.10	0.8 (0.63, 1.01)	0.049
Constant			1244.4 (358.88, 4314.92)	<0.001
Gamma			0.63 (0.58, 0.67)	

Table 3: Proportional hazard assumption checking for the covariates.

Covariates	Chi-square value	Df	p value	Does PH assumption hold?
Age	9.784	1	0.002	No
Gender	0.399	1	0.53	Yes
College/faculty	86.321	7	<0.001	No
Region	5.727	5	0.33	Yes
CGPA	1.478	3	0.69	Yes
Residence	1.321	1	0.25	Yes
Studying the preferred fields of study	0.372	1	0.54	Yes
GLOBAL	94.451	19	<0.001	No

Table 4: Summary of AIC and BIC values for different survival models.

Model	Log-likelihood for the null model	Log-likelihood for the current model	Df	AIC value
Weibull	−1236.86	−1079.78	16	2191.555
Log-normal	−1231.62	−1081.37	16	2194.743
Log-logistic	−1231.59	−1078.12	16	**2188.247**
EXP	−1237.98	−1092.12	15	2214.241
CPHM	−3380.04	−3245.89	14	6519.771

4. Discussion

Despite all the advantages of the Cox model [22] in terms of modeling time-to-event data such as waiting time to first employment, it has drawbacks when the proportional hazard assumption is violated. When the assumption of proportional hazard was violated, fully, parametric AFT models can be used as an alternative to model time-to-event data such as time to first employment. In this study, the accelerated failure time (AFT) model was employed to analyze time to first employment data. Among the parametric AFT models, the log-logistic parametric model fitted the data well. The median time to first employment of the graduate was 15 months, which is a longer time compared to the study conducted in Sri Lanka where nearly 50% of the graduates got their first job by 12 months after their graduation [34]. This variation would have happened due to the differences in the study areas and years of graduation.

The study revealed that males had shorter unemployment spells than that of females. This finding is similar to the previous studies conducted in Tanzania [35], but it contradicted a study conducted in Ethiopian by Kong and Jiang and in China [36, 37], which showed that female graduates are more likely to enter the labor market ahead of males. This is possibly attributed to the difference in study time and place. The result also revealed that graduates who were in a higher CGPA category had shorter unemployment spells. This result is in line with the tracer study results of Bahir Dar University graduates, Ethiopia [38], and a study conducted in China [14]. One possible reason could be, in Ethiopia, the number of job applicants is usually much higher than the number of vacancies where employers use academic grade (CGPA) as an elimination criterion; thereby, graduates with a better achievement have more chance of being recruited as possible candidates. Moreover, employers of graduates think that graduates with a better academic performance, usually measured by cumulative grade point average, as hard-working and smart candidates who can perform better at their company. In result, it was also revealed that graduates who studied their preferred fields had shorter waiting time to first employment compared to those compared to graduates who did not study their preferred fields. This is in line with a study performed in Ethiopia by Cox [22]. This is the fact that students who studied usually have enough motivation to study, thereby achieving better, whereas lack of interest in the field of study can lead to academic failure. In the study, it was revealed that the probability of getting a job decreases monotonically with time. This result is in line with a study conducted in Croatia [39]. This is the fact that employers may think that long-term unemployed face loss of skills and the substantial expenditures that are necessary to restore these skills [40].

5. Conclusion

This study is based on a dataset on the waiting time to first employment derived from DMU 2018 graduate tracer survey data to examine the comparative performances of Cox and parametric models for the analysis of time to first employment. Although parametric models assume a specific distribution for the event (waiting time to first employment), they can be used as an alternative model for the Cox model when the proportional hazard assumption fails. In this particular study, the log-logistic parametric model yielded the smallest possible AIC and could be taken as the best fitted model for the data well as compared to other parametric models. Based on the log-logistic model, graduates' average time span of unemployment was significantly affected by the graduates' gender, age, college/faculty, cumulative grade point average (CGPA), place of residence, region where the graduates were from, and achievement (measured by CGPA). Crudely, only 50% of the graduates managed to find their first job by 15 months after their graduation date, which is far less than the university's target where about 69% of its graduates could secure their first job by 12 months after graduation.

6. Recommendation and Policy Implications

The estimated 12 months employment rate (44%) is far below the university's target (69%). Hence, for effective transition of graduates to the labor market, the university should have a fully functioning career service office, which is staffed with ample professionals and optimal resources to provide training on job hunting; to deliver the soft skills effectively; and to arrange job fair programmers, to strengthen relationships with employers. The university together with its stakeholders should encourage the provision of entrepreneurship educational practices and trainings to cultivate an entrepreneurial mindset among graduates and turn them into job creators instead of job seekers. Moreover, Ethiopian Ministry of Science and Higher Education should work with ministry of labor affair and other stokeholds to align the education programs in line with the demand of the labor market.

Abbreviations

KM: Kaplan–Meier
DMU: Debre Markos University
CGPA: Cumulative grade point average
AIC: Akaike information criterion
AFT: Accelerated failure time
PH: Proportional hazard.

Data Availability

The datasets used to support this study are available from the corresponding author upon reasonable request.

Ethical Approval

The researchers have got permission from the office of the delivery unit, Debre Markos University, to use graduated tracer survey data without fabrication and falsification of data.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

MGA contributed to the study concept and design of the statistical methodology, performed the analysis, interpreted the data, and wrote the first draft of the manuscript. AA contributed to the study on critical revision of the manuscript, and AW assisted in analyzing the study and wrote up the manuscript. All the authors read and approved the final manuscript.

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Supplementary Materials

R codes used for the analysis of the waiting time to first employment of new graduates using the survival model (PDF 288 kb) are given. (*Supplementary Materials*)

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