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"Working While Studying" and Educational Mismatching Among Youth: Evidence From Zambia

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Abstract

This paper analyzed the effect of working while studying in college and university on educational mismatching in the Zambian labor market. The study used the 2014 School to Work Transition Survey data and estimated a range of extended ordered probit regression models that took self-selection and sample-selection bias into account. Our results showed that working while studying significantly reduced the likelihood of being undereducated for the job but increased the likelihood of being overeducated for the job, implying that additional support to enable youth to get exposure to the right amounts and types of work during college or university studies could potentially increase productivity by ensuring job matching. Stakeholders designing work-based skills-development programs should consider the possible counter effects of combining learning and working. Furthermore, there is a need for investment in guidance mechanisms for students wishing to combine work and learning.

JEL: C26; I21; J24; J16

Keywords: Working while Studying, Youth, Educational Mismatch, Zambia

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I. Introduction

1.1 Context of the study

Work-based experience or working while studying offers students the opportunity to gain additional human capital such as skills and experience that could have a bearing on future labor-market outcomes (Ruhm, 1997). Combining study with work also provides students the income to satisfy their consumption needs (Baert et al., 2016; Neyt et al., 2019). Furthermore, in country with high unemployment, matching the skills of the labor force is even more crucial. Job mismatching has an effect on productivity, both at firm level as well as, at industry or national level. Recent studies have explored and established that skills and qualification mismatching affect both within-firm productivity and allocative efficiency that affects aggregate productivity (McGowan & Andrews, 2015). One key factor in addressing labor-market mismatching is whether the individual possesses the requisite skills for employment.

Evidence has suggested that exposing young people to a work environment while they are still studying can help them acquire the skills that will not only reduce their job-search period but also enhance their chances of being better matched in employment. Pre-graduation work experience or working while studying has the potential to provide students with a shorter school to work transition through acquired specific labor market skills, networks, and guidance in terms of career goals and aspirations (Brooks et al., 1995; Maertz, Stoeberl & Marks, 2014; Dedehouanou et al., 2019; Nilsson, 2015). More broadly, students' exposure to work enables them to align their career interests with their goals at a much earlier stage in life, promoting career planning and alignment (Maertz, Stoeberl & Marks, 2014). Working while studying can link potential graduates to professional networks or enhance these relationships, which, in turn, improves the quality of the match between graduates and employers (Holford, 2017).

Although about 55% of employed youth in Zambia have jobs that match their level of education, a substantial share (26%) is overeducated for the positions they hold (Chigunta, Chisup & Elder, 2013). The consequence of mismatching between level of education and type of job means that youth do not contribute their full productive potential. Despite growing evidence on the role of working while studying on labor-market outcomes in developed countries (Holford, 2017; Saniter & Siedler, 2014; Jewell, 2014), little work has been done in developing countries. Related studies done in Benin by Dedehouanou et al. (2019) and Nilsson (2015) established that youth who worked while studying had an advantage in the work-to–school transition.

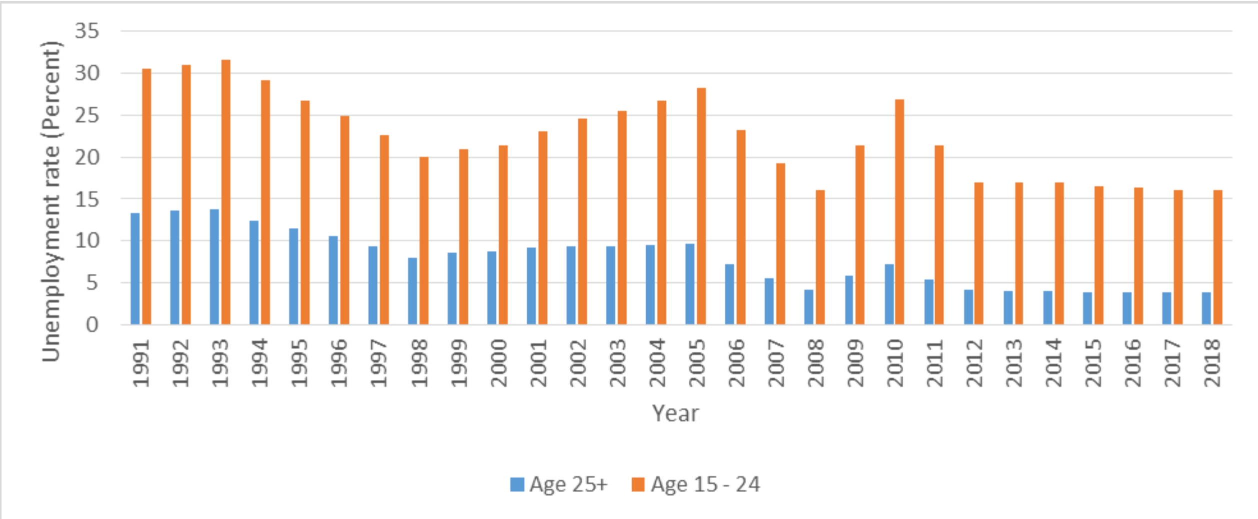
Despite several interventions aimed at tackling youth unemployment in Zambia, such as the National Youth Employment and Job Creation Strategy in 2013 and the Action Plan for Youth Empowerment and Employment (an implementation tool for National Youth policy; Ministry of Youth and Sport, 2015), youth unemployment is still high. A broad consensus exists that the reason for high levels of youth unemployment is that current measures have focused on the labor market, whereas the causes of employment mismatching and persistent youth unemployment come earlier, in the formative stages of an individual's employment career (that is, pre-graduation.) Recent developments have focused on improving training and prequalification work exposure, however. For instance, Zambia has embarked on sector reforms in higher education, including a review of Technical Education and Vocational Entrepreneurship Training (TEVET) policy, a review of apprenticeship policy, and other skills-development-focused interventions, such as a Work-Based-Learning Framework intended to bridge mismatching by focusing on the pre-graduation work exposure (apprenticeships and internships, e.g.) that complements college and university training. The key assumption in all these efforts, however, has been that early work exposure will help young people make career choices and enable them to be better matched with future employers, as studies mainly from developed countries have illustrated.

With the foregoing as a foundation, we sought to examine the causal effect of working while studying on educational mismatching in Zambia. Educational or vertical mismatching occurs when the level of education or qualification is more or less than is required for a job (Sloan, 2014, Proctor & Dutta, 1995). We controlled for sample-selection bias into employment for (mis)matched youth and self-selection into pre-graduation work. In the literature, differences in labor-market outcomes based on gender have been observed (Croson & Gneezy, 2009; Blau & Kahn, 2000). Similar to Saniter and Siedler (2014), we also examined the heterogeneous effects of pre-graduation work experience on educational mismatching as a result of gender. The analysis used the 2014 School to Work Transition Survey. As Zambia implements various programs in support of internships and apprenticeships as part of the Seventh National Development Plan (7NDP) strategies, such evidence is important.

Background on Youth Unemployment in Zambia

Youth unemployment in developing countries, even among educated youth, remains particularly high (World Bank, 2014). Global youth unemployment in 2017 stood at 13%, about three times the adult rate (ILO, 2017)). In Zambia, youth unemployment rates are five times higher than adult rates. Youth aged 15-19 have the highest unemployment rate at 17.1%, followed by 20-24 year-olds (13.8%), 25-29 year olds (9%), and 30-34 year olds (5.7%) compared to a national average of 7.4% (Labor Force Survey Report, Central Statistics Office, 2014). Moreover, youth aged 15-24 are more likely to be unemployed than those aged 25-34 (Bhorat et al., 2015). Modelled ILO estimates have indicated that the youth unemployment rate has been stable at 15% since 2012 (Figure 1).

Figure 1: Zambia Adult (25+) and Youth (15-24) Unemployment Rate (1991-2018)



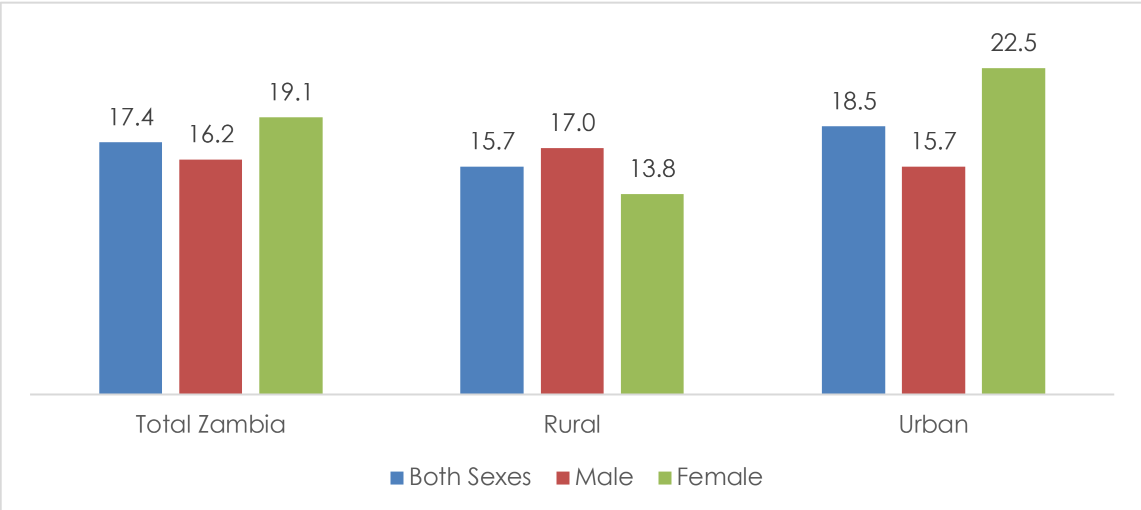
Source: World Bank Development Indicators (modelled ILO estimates).

Recent country estimates have indicated that, in 2018, the average youth-employment rate was 17.4% (Figure 2).[1] Such national average statistics mask heterogeneity by gender and region, however. Generally, unemployment is higher in urban vs. rural areas, but variations

[1] The difference in modelled ILO estimates in Figure 2 and country-level estimates from survey data in Figure 3 could be related to differences between survey and administrative data.

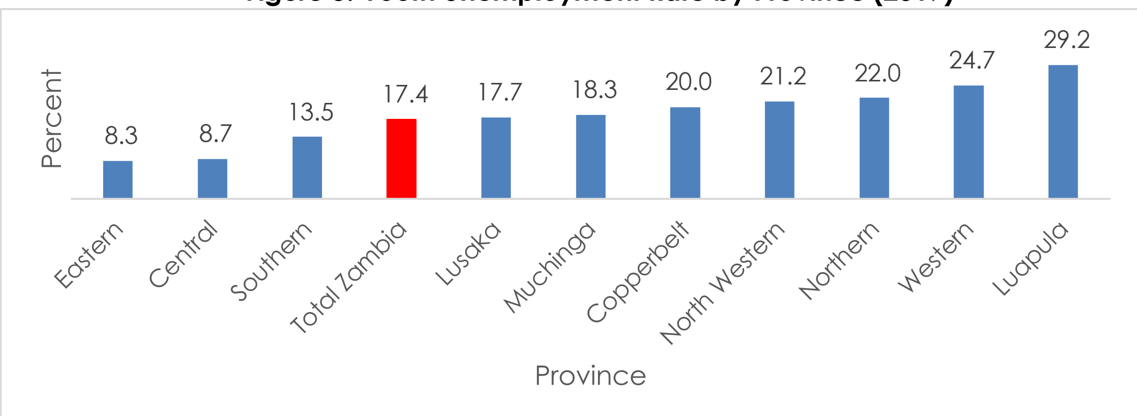
by gender are also found within the rural/urban settings as well as by province (Figure 3). Central to high youth unemployment has been the challenge of educational mismatching among young people entering the labor market, which contributes to the delay in finding a first job or satisfying job. With the gradual increase in the supply of college and university graduates and low absorption rate in the labor market, youth in Zambia tend to take up jobs for which they are over-qualified (Chigunta, Chisup & Elder, 2013).

Figure 2: Youth Unemployment Rate by Rural/Urban and Sex (Zambia 2017)



Source: Zambia Central Statistics Office (2018).

Figure 3: Youth Unemployment Rate by Province (2017)



Source: Zambia Central Statistics Office (2018).

1.2 Research questions

The study sought to examine the following research questions: What is the causal effect of working while studying on educational mismatching in Zambia? Are there differences in effects using the subjective or empirical approach?

II. Literature review

2.1 Theoretical Perspective

The theoretical relationship between educational mismatching and work experience while studying can be espoused using human-capital, screening, signaling, and networking theories. The human-capital theory postulates that pre-graduation work exposure increases employees' skill level and thus leads to higher chances of being employed and earning higher wages (Mincer, 1975; Becker, 1975). Pre-graduation work exposure in the form of working while studying or internships leads to a rise in specific human-capital skills, which are likely to enable students to find a job for which they are both horizontally and vertically matched (Simon & Warner, 1992; Negrut, Mihartescu & Mocan, 2015). This is because pre-graduation work exposure provides hands-on work experience that not only reduces skill gaps but also facilitates training relevant to labor-market demand (Klosters, 2014).

Based on screening theory, pre-graduation work experience can function as a device for employers to identify best-suited students for specific positions (Stiglitz, 1975). According to Wolbers (2003), it allows firms to reduce selection and allocation costs while enabling them to provide firm-specific training to prospective employees. Once eligible individuals have been identified, they are assigned to a job for which they are matched after graduation. In essence, access to temporary employment in a firm increased chances that individuals would have access to employment that fit their training in terms of both field and level of education (Wolbers, 2003).

Signaling theory, as developed by Spence (1973), provides some insights into the relationship between skills mismatch and pre-graduation work exposure. A major concern with recent graduates and school leavers is that they lack relevant experience that would allow them to apply for and acquire jobs for which they are trained (International Youth Foundation, 2013). Additionally, for higher levels of education, credentialism theory questions whether post-secondary education provides the skills necessary for employment. The theory asserts that skills are largely acquired on the job, and employers see education only as a predictor of the future productivity and trainability of employees (Boudarbat & Chernoff, 2010). Therefore, the combination of academic and practical skills might signal higher ability and potential productivity to prospective employers, making it more likely that individuals will be hired for jobs for which they are vertically matched.

Because pre-graduation work experience builds not only on human capital but on social capital, the social-capital or network theory postulates that day-to-day relationships and associations have a bearing on an individual's future endeavors because they create influences that advantage job-seekers (Claridge, 2004). Studies show that work experience during training fosters social capital for individuals (Murillo, Quartz & Del Razo, 2016). In essence, we expected that working—in a field that was related to the individual's area of specialization or focus—while studying would reduce the likelihood of a mismatched job.

On the other hand, a negative transmission mechanism also exists. Working while studying, particularly during the school session, can lead to low academic performance and lower educational attainment, which in turn reduce the chances of being matched for a job. The negative impact of working while studying on academic performance and educational attainment of high school seniors was documented by Ruhm (1997). Similarly, Jewel (2014) also found that working while studying had a negative impact on academic performance among graduate students in the United Kingdom. A literature review by Neyt et al. (2019) found that student employees may experience more adverse effects on educational choices and behavior than on educational performance. In general, studies on the effect of student employment on later labor outcomes find non-negative results (Neyt et al., 2019; Baert et al., 2016).

2.2 Empirical Review

Few studies have examined the relationship between working while studying and job match (Jewell, 2014; Saniter & Siedler, 2014), particularly in the context of developing countries. The evidence has suggested that pre-graduation work exposure enhances students' job and social skills and improves their career path decisions. In a study to determine wage outcomes resulting from mandatory internships in Germany, Saniter and Siedler (2014) found internships had a positive and significant impact on wage returns. The study, however, found little evidence that internships improved job matching or had an impact on graduates' occupational choices. Similarly, studies by Le Saout and Coudin (2014), Withanawasam and Lalaine (2012), and Al Samman and Fakhro (2017) found that internships enabled students to find work faster in France, Sri Lanka, and Bahrain, respectively. Di Paolo and Matano (2016) found that job quality was improved by pre-graduation work experience in the field of study for students in the Spanish region of Catalonia. However, Wolbers (2003) found that individuals that acquire specific human capital in the form of school or work-based vocational training were less likely to end up in an unmatched job.

Some studies have found that pre-graduation work exposure reduced the time spent looking for employment (Vélez & Giner, 2015; Le Saout & Coudin, 2014; Withanawasam & Lalaine, 2012; Al Samman & Fakhro, 2017; Dedehouanou et al., 2019; Nilsson, 2015). Cameroon et al. (2013) found that work integrated learning in Economics, which incorporates formal learning and workplace experience, had a positive effect on labor-market outcomes. Similarly, Weiss, Klein, and Grauenhorst (2014) found that only field-related and voluntary work experience had positive effects on labor-market integration in Germany.

However, not all studies have found a positive relationship between internships/ temporary work and employment outcomes. Using German data, Harms (2017) found that internships had negative transitory effects, which died out within five years of entering the job market. Similarly, Klein and Weiss (2011) found no evidence that compulsory internships in Germany had a positive impact on wages, employment history complexity, or duration before the first significant job. The authors found that internships did not alleviate disadvantages in labor-market integration for less well educated graduates. In the United States, Carnevale et al. (2015) found that combining work and learning could be beneficial, especially if the work was in the same field as the subject the respondent had studied. The authors argued, however, that working while studying tended to negatively affect learners who were less privileged and had to put in additional work hours for survival. Similarly, Baert et al. (2016) found a negative association between hours of student work and the percentage of courses passed for work-oriented students. Arguably, work experience while studying, in areas related to an individual's field, is beneficial, and this notion has often been supported by policymakers and practitioners, particularly in developed countries (Teichler, 2011).

Importantly, individual labor-supply characteristics are correlated with factors such as ability and motivation, which also affect labor outcomes. For instance, unemployed youth are different from the employed in such observable characteristics as education, and in unobservable characteristics such as ability, motivation, and eagerness to find a job. Some studies have proposed various approaches for dealing with the differences in observable characteristics (propensity-score matching or coarsened exact matching); others have used instrumental variables to deal with sample-selection bias (Ghignoni & Verashchagina, 2014; Kim & Park, 2016).

The costs of mismatching affect individuals, firms, and the overall economy because they influence wages, productivity, and innovation. At the individual level, mismatching can affect earnings if competition causes individuals to take jobs for which they are less qualified. The effect can be long-lasting or even permanent if, for instance, human capital depreciates (Brunello & Wruuck, 2019). The job-search strategies of qualified workers who accept lower-paying jobs for which they are less qualified have a crowding-out effect on opportunities for less-qualified workers (Arseneau, 2014). Evidence from developing countries has shown that over-qualified individuals earned about 3% less than individuals with similar qualifications but who were matched for the jobs they hold, and that underqualified workers earned at most 3% more than workers with similar qualifications who were matched for their jobs (Brunello & Wruuck, 2019).

Furthermore, studies have shown that educational mismatching reduced job satisfaction and could result in increased absenteeism and loss of productivity. The expectation has been that overeducated workers would invest less in additional training compared to individuals who were well matched with similar qualifications (Verhaest & Omey, 2006). At the firm-level, mismatching is costly because overeducated workers are more mobile than individuals who are well matched, resulting in higher recruitment and training costs. At the aggregate level, mismatching leads to loss in average productivity by distorting the optimal allocation of resources across firms (Brunello & Wruuck, 2019).

Although vast evidence from developed countries exists regarding pre-graduation work experience, internships, and educational mismatching, there has been a paucity of literature in the context of developing countries, especially in Sub-Saharan Africa. In most developing countries, the labor force is engaged in the informal sector, and it remains unclear to what extent working while studying influences educational mismatching in such a context. In this study, we examined the effects of pre-graduation work experience on educational mismatching in Zambia, using a unique survey that collected data among youth aged 15-29 in 2012 and 2014. We accounted for self-selection and sample-selection bias by using instrumental variables in a structural-equation framework.

III. Methodology and Data

3.1 Economic Modelling

Our analytical approach for examining the causal effect of working while studying on educational mismatching is based on a structure, which assumes that a youth is either employed or unemployed. In the next stage, educational mismatching is then determined for the employed youth based on three categories: undereducated, matched, or overeducated. Intuitively, the modelling approach is sequential: the first stage is a binary model for employment, and the second stage is a categorical model for educational mismatching. Firstly, educational mismatching is observed only for the employed sample, and this leads to a sample selection bias because of the non-random allocation of the sample (Cameron & Trivedi, 2005). Unemployed youth may be different from employed youth in such observable characteristics as education. Moreover, employment status is correlated with other unobservable factors such as ability, motivation, and eagerness to find a job, which also affect employment status. Given that, this proposed specification potentially implies a selection bias as a result of the exclusion of the unemployed sample. Second, the endogeneity or self-selection of youth who work while studying generates a bias.

Therefore, by examining the causal effect of participation in pre-graduation work on educational mismatching, the three following important econometric issues need to be addressed: 1) the nature of the ordered categorical nature of the dependent variable; 2) sample-selection bias, given that educational mismatching is not observed for the entire sample; and 3) endogeneity because motivated youth may decide to work while studying.

Given that the dependent variable (educational mismatching) takes the form of an ordered categorical variable, it can be modelled using an ordered probit or logit (Long, 1997). However, the estimated coefficients may be biased as a consequence of selection bias arising from exclusion of unemployed youth (unobserved) and endogeneity potentially arising from the work/study variable.

To deal with selection bias and potential endogeneity, we used an extended ordered probit regression, which accommodated any combination of endogenous covariates, nonrandom treatment assignment, and endogenous sample selection (Wooldridge, 2010; White, 1996).

Let y_i be the ordinal variable that measures educational mismatching. The variable y_i is generated according to a continuous latent variable model

$$y_i^* = \theta Work\_S_i + X_i\beta + \varepsilon_i \qquad (1)$$

where the observed response y_i is determined by a threshold model

$$y_i = \begin{cases} missing\ , & if\ employed_i = 0, \\ 0, & if\ y_i^* \leq \mu_0 \quad and\ employed_i = 1 \\ 1, & if\ \mu_0 \leq y_i^* \leq \mu_1\ and \quad employed_i = 1 \\ 2, & if\ \mu_2 < y_i^* \quad and\ employed_i = 1 \end{cases} \qquad (2)$$

where $Work\_S_i$ represents work/study, a potentially endogenous dummy variable, and mismatching is only observed if a selection rule $employed_i$= 1 is met. Then, y_i is educational mismatching categorized as: 0=undereducated, 1=matched, and 2=overeducated; y_i^* is the unobservable true variable representing educational mismatching of individual i; X_i is a vector of variables that explain the variation in educational mismatching; β is the vector of coefficients; μ_i is the parameter thresholds to be estimated; and v_i is the disturbance term that is assumed be independent standard normal. Therefore, the probability that an employed youth would fall into the *jth* educational mismatching can be estimated using an ordered probit model (Wooldridge, 2010) given by:

$$P_{ij} = P(y_i = j) = P(\mu_{j-1} < y_i^* \leq \mu_j) = F[\mu_j - E(y_i^*)] - F[\mu_{j-1} - E(y_i^*)]\ j \in \{1,2,3\} \quad (3)$$

where F is the standard normal cumulative distribution function and $E(y_i^*)$ is the expected value from the mismatch function (y_i^*). Hence, the marginal effect of an increase in a regressor X_r on the probability of j educational mismatching is given by:

$$\frac{\partial p_{ij}}{\partial X_{ri}} = \{F'[\mu_{j-1} - E(y_i^*)] - F'[\mu_j - E(y_i^*)]\}\,\beta_r \;\; j \in \{1,2,3\} \quad (4)$$

Equations 3 and 4 were estimated using a maximum simulated likelihood (Gregory, 2015).[2] We modelled the extended ordered probit equations using the "*eoprobit*" command in STATA 15 (StataCorp, 2017). The work/study and selection variable (employed) is also generated based on the continuous latent variable model

$$employed_i^* = \omega Work\_S_i + C'\gamma + \varepsilon_{si} \quad (5)$$
$$Work\_S_i^* = Z'\alpha + \varepsilon_{wsi} \quad (6)$$

where the two latent variables are such that $employed_i = 1\,(employed_i^* > 0)$ and $Work\_S_i = 1\,(Work\_S_i^* > 0)$. Z is a vectors of the covariates that affect selection and work/study, respectively, and ε_{ji} (j= s, ws) are unobserved errors, which are normally distributed.

To avoid the tenuous identification problem even though the model was identified by functional form, we specified a set of exclusion restrictions. The variables, which were proposed to be additional covariates in the selection-bias equation, were the unemployment rate by ward and mother's education. The argument for using these control variables was that youth employment would depend on the unemployment rate in area of residence and mother's education. Logically, we expected that youth residing in wards with high unemployment rates were more likely to be unemployed than their counterparts in wards with relatively lower unemployment rates. In the literature, mother's education has been linked to improvements in child health outcomes (Shahraki et al., 2018). Improved child health outcomes, in turn, have been associated with the development of cognitive skills, which have a bearing on the future acquisition of human and social capital (Currie, 2009). Social and human capital are key factors in finding employment. We thus expected that youth whose mothers had completed higher levels of education were less likely to be unemployed vs. youth whose mothers had low levels of education.

As mentioned earlier, there is potential endogeneity for the decision to take up pre-

[2] For extended theoretical discussions of the extended probit model, refer to Wooldridge (2010) and White (1996).

graduation work because more able and motivated students can do so. Analysis of the relationship between working while studying and educational mismatching, without accounting for these unobservable characteristics, suffers from selection bias. Similar to Saniter and Siedler (2014), we used instrumental-variable techniques to address the selection problem and identify the causal effect of working while studying on educational mismatching among the youth in Zambia.

Overall, we specified a multi-equation model that, when estimated jointly, was intended to address both endogeneity bias and selection bias. Individuals' decisions to combine work with school (7) were followed by the employment decision (8) and, for those who were employed, there was a question whether the job matched education (9). Mismatching was only observed for employed youth. These equations are presented below:

$Work\_S_i = Z_i\alpha + +\varepsilon_{wsi}$	Endogenous treatment equation	(7)
$Employed_i = \omega Work\_S_i + C'\gamma + \varepsilon_{si}$	Selection equation	(8)
$MIS_i = \theta_1 Work\_S_i + X_i\beta_2 + \varepsilon_i$, *if employed=1*	Outcome equation	(9)

MIS_i is the ordered categorical outcome of interest (educational mismatching), $Work\_S_i$ is a dummy variable for working while studying, $Employed_i$ is a dummy variable equal to 1 if employed. That is, the outcome model (Equation 9) is observed only for youth who were employed (employed=1). Z_i is the exclusion restriction, C_i represents the vector of variables to control for selection bias, and X_i is a vector of control variables, which includes the constant term. ε_i, ε_{wsi}, and ε_{si} are error terms for the outcome, endogenous treatment equation, and selection equations, respectively, and they are normally distributed.

For the endogenous treatment equation, we used three exclusion restrictions: number of children that a youth has, father's (or household head's) occupation, and father's education. These instruments were chosen on the basis that they might directly influence the decision to engage in work while studying but did not directly affect job matching of youth. For instance, if the father (or household head) had an occupation in subsistence agriculture or ran a family enterprise, this could have compelled youth to engage in work activities related to the family's welfare during their studies. Some concerns may arise regarding the strength and validity of these instruments, however. For the variable denoting the number of children that a young person had, we expected that, in the context of developing countries, this argument would hold only for women and could possibly suggest that the instrument was weak. For father's occupation and father's education, we anticipated that some correlation between these variables and educational mismatching might occur, which would threaten validity.

To supplement the chosen exclusion restrictions, we constructed an artificial instrument based on the two main conditions for good instruments (Cameron & Trivedi, 2005; Le Gallo & Páez, 2013), which were:

$IV \Leftarrow \varepsilon_1$: This means that $Corr(\varepsilon_1, IV_i) = 0$ for $i = 1 \ldots T$. (T is the number of instrumental variables). In other words, the IV_i will not contribute in explaining the educational mismatching, even through the common unobserved factors.

1. $IV \leftarrow \varepsilon_1$: ($\leftarrow$ denotes the high correlation) that is, the IV variables must explain as much as possible the component Y_2.
2. Based on these two conditions, we follow two steps. For the first step, we construct an artificial instrument T_p presented by equation 10 below that satisfies both the above stated conditions. The first part of the equation satisfies the exogeneity condition that requires that the instrument must not be directly correlated with the dependent variable. The expression $\sum_{c=0}^{2} \varepsilon_{p,c} * [p \in c]$ denotes that for each person (p) in each category (c) of the dependent variable (educational mismatching) we randomly assign a number from the uniform distribution. This allowed us to fulfil the orthogonality property because we did not expect randomly assigned values to be correlated with the educational mismatching variable.

The second part of the equation satisfies the validity property, which requires that the instrument must be highly correlated with the independent variable being instrumented. To do this, we specified a relationship between the endogenous variable "working while studying" (denoted by WS_p) and the instrument in the next part of the equation. The two parameters $\alpha$and βdenote the magnitude of the relationships among the instrument, the common unobserved factors, and the dependent variable (educational mismatching), respectively. When parameter β was high, the correlation between working while studying and educational mismatching was also high. However, when parameter α was high, the correlation between working while studying and common unobserved factors was high.

$$T_p = \sum_{c=0}^{2} \varepsilon_{p,c} * [p \in c] + WS_p * \left(\alpha + \beta \vartheta_p\right) \text{(10)}$$

Second, to obtain our instrumental variable, we regressed (logit) work/study on T_p and the rest of regressors in the working while studying equation. Using the predict option in Stata, we obtained linear predictions from the regression to be our final artificial instrumental variable. While the artificial instrument was theoretically valid, there were concerns about its lack of practical or empirical validity (Angrist & Pischke, 2008). To ensure robust results, we tested the validity and relevance of the instruments using the "rivtest" package, which is a post-estimation test for "ivprobit" in Stata. For further validation, we also used the post-estimation tests of "ivreg2," which runs an instrumental variable regression in Stata 15 (StataCorp, 2017).

3.2 Data

Our analysis was based on the 2014 School to Work Transition Survey (hereafter, SWTS) obtained from International Labor Organisation's Work4Youth project. This unique, nationally representative survey provided in-depth cross-sectional data on the population aged 15-29 that may not have been available in Labour Force Surveys. The SWTS contained five modules with detailed information on personal, family, and household information; formal education/training and aspirations; activity history; and specific sections for young workers and non-working youth.

The 2014 SWTS used the sampling framework of the 2010 census conducted by the Central Statistical Office in Zambia. In the survey, a multistage cluster-sampling technique was used in which the first sampling unit was a cluster or standard enumeration area. The number of clusters in each of the ten provinces in Zambia was determined to be proportional to the total youth aged 15-29 in the province. The total number of youth per province was calculated using 2010 census single-age projections.

The 2014 SWTS included a sample of 3,225 youth aged 15-29. The key variables of interest were constructed based on the following questions from the survey: Work_study: *Did you ever work while you studied?* A potential concern was that the variable "working while studying" could include working during the school year and occasionally during breaks or outside the school season. This could have resulted in heterogeneous effects of working while studying based on the duration and timing of the work. Data limitations, however, made it impossible for this study to disentangle these effects.

3.2.1 Measuring Educational Mismatching

Three main alternative approaches to the measurement of educational mismatching have been reported in the literature: 1) the objective method compares the required level and type of employment with the actual education obtained by an individual; 2) the subjective method compares workers' own assessments of the level of education required for the position with their actual level of education; 3) the empirical method compares either the mean or modal educational level of all individuals in that occupation to their actual education level.

The subjective criterion is constructed based on self-reported evaluation by respondents about how they perceived themselves in the work place. The results presented in this paper were generated using the perception or subjective measures as well as the empirical measure. The subjective measure was reported by the survey respondents as follows: *Do you feel your education/training qualifications are relevant in performing your present job? A) Yes, they are relevant B) No, I feel overqualified, C) No, I experience gaps in my knowledge and skills/need additional training.* The responses for A were coded as matched, B as overeducated, and C as undereducated.

Based on an ordered approach, we coded undereducation as 0, matched as 1, and overeducation as 2. While ordering from undereducated to matched (0 to 1) could be justified as moving to a better position, ordering from matched to overeducated (1 to 2) did not necessarily imply moving to a better position. Both undereducation and overeducation have been associated with a loss in productivity (Vroom, 1964; Dolton & Silles, 2008). Additionally, overeducated employees may face a wage penalty from being in a job for which they are over educated (McGuinness, 2006). We justified this ordering based on human-capital theory, however. Undereducated workers have the least stock of educational human capital whereas overeducated people have the highest.

In the objective method, the basic idea was to use the International Standard Classification of Occupations (hereafter, ISCO) occupational group classification by education level, the actual education level attained, and the actual occupation category to generate three mismatching categories for employed youth. An employed youth was classified as overeducated if the actual occupational position required a lower educational level, matched if the occupational position required the same educational levels, and undereducated if the position required higher education levels.

We did not adopt the objective method as a result of important data restrictions. Particularly, the ISCO-08 classification by educational level uses broad classifications (ten) of occupations, and education was problematic for this study context. For instance, according to the ISCO-08 and ISED-97 classifications, individuals who fall within the broad occupational categories of clerks, sales, and service are expected to have at least a secondary education. In a developing country such as Zambia, however, this may not be the case because individuals with lower education can and usually do perform these jobs.

The empirical approach, which uses the distribution of schooling in a given occupation, requires that the mode or mean within a group be compared to the individual's schooling level. Consequently, we defined an individual with a schooling level that was more than one standard deviation above the mean as overeducated—undereducated if the level of schooling was one standard deviation below. For the mode, an individual with schooling above the mode was considered overeducated, an education level equal to the mean was considered matched, and a schooling level below the modal level of schooling was considered undereducated.

We therefore generated a dependent variable coded as 0 to represent undereducation if the highest level of education attained, measured in categories, was less than 1.05 times one standard deviation from the mean. Matched education was coded as 1 when the level of education attained was within 1.05 times one standard deviation from the mean, and overeducation was coded as 2 if the level of education was higher than 1.05 times one standard deviation from the mean of all individuals within the occupation category. The method was applied to each occupational subgroup defined in the ISCO-08. In the next section, we present the results of both the empirical and the subjective approach as complementary information.

IV. Results

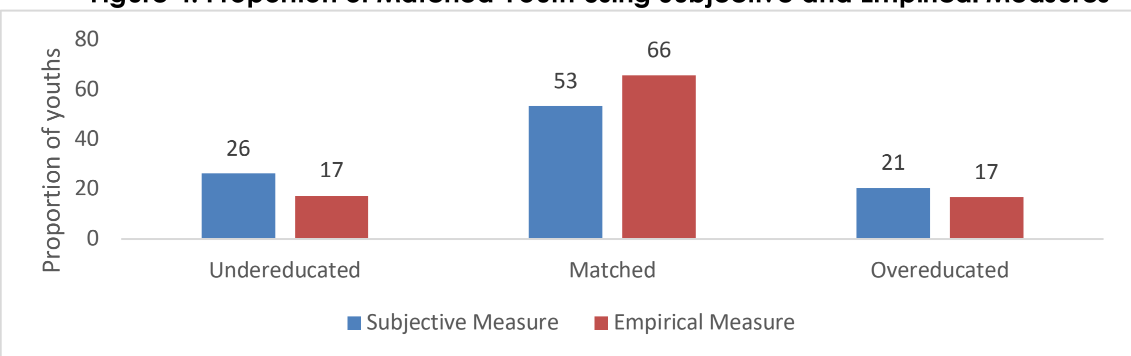
4.1 Descriptive Statistics

Table 1 and Figure 4 summarize the main socioeconomic and demographic characteristics of sampled youth at the time of the 2014 STWT survey. The study mainly included young people from 20-24. The summary statistics showed that unemployment tended to be high among youth aged 20-24 and was lowest among in the sampled population among youth aged 25-30. This could be because most students entered the labor market between ages 20-24 and their integration into the labor market took time.

The majority of those who were working were matched using both empirical and subjective measures as indicated in Figure 4. The descriptive statistics in Table 1 further show similar proportions of matched and mismatched youth by gender, an indication that job mismatching among youth in Zambia us independent of gender. However, other studies have shown that overeducation is higher among women (Rahona-López & Pérez-Esparrells, 2013).

Additionally, our results showed that educational matching among youth was highest among 20-24 year olds and lowest in those aged 15-19. Furthermore, the results showed that undereducation rose with movement across the age groups while overeducation decreased.

Figure 4: Proportion of Matched Youth Using Subjective and Empirical Measures



Source: Authors' compilation from the Zambia SWTS 2014.

Table 1: Descriptive Statistics

Age groups	*15-19*	*20-24*	*25-29*
Number of observations	586	936	578
Sample	27.90	44.57	27.52
Men	26.65	46.60	26.75
Women	29.29	42.33	28.39
Unemployed	13.13	14.85	11.07
Women	12.93	15.56	8.81
Women	13.70	13.98	13.43

Subjective Educational Mismatching (%)	Undereducated (0)	Matched (1)	Overeducated (2)
Number of Observations	360	930	341
Sample	22.07	57.02	20.91
Men	21.38	57.58	21.04
Women	23.28	56.23	20.49
By Age Group			
15-19 years old	21.06	55.30	23.64
20-24 years old	21.12	58.96	19.92
25-29 years old	25.35	56.07	18.58
By Education			
Primary education	32.67	54.72	12.61
Skills training center	37.62	15.14	47.25
Secondary school	24.47	52.20	23.33
College certificate/diploma	6.80	59.43	33.76
University	14.85	78.36	6.79
Post-graduate degree	0.00	0.00	100.00
By Province			
Muchinga	28.83	40.88	30.28
Southern	23.92	49.79	26.29
Lusaka	27.89	51.88	20.23
Northern	28.24	57.00	14.76
Eastern	24.73	57.79	17.48
Central	15.39	57.91	26.70
Luapula	12.74	58.22	29.04
Western	25.78	59.39	14.84
Copperbelt	15.10	65.49	19.41
Northwestern	17.31	70.02	12.68
National	22.29	56.94	20.77
By Industry			
Public administration and defense	29.11	27.22	43.67
Transportation and storage	41.22	44.38	14.41
Human health and social work activities	13.52	46.91	39.57
Water supply; sewage, waste management	0.00	47.05	52.95
Electricity, gas, steam and air conditioning supply	21.26	49.32	29.42
Real estate activities	50.31	49.69	0.00
Construction	28.07	51.01	20.92
Accommodation and food service activities	30.11	53.54	16.41
Professional, scientific, and technical activities	12.68	54.36	32.96
Other service activities	24.09	54.61	21.29
Activities of households as employers	18.68	56.32	25.01
Agriculture, forestry, and fishing	22.85	58.53	18.62
Information and communications	18.40	58.54	23.06
Wholesale and retail trade; repair of motor vehicles	19.89	58.67	21.44
Manufacturing	17.28	61.00	21.72

Education	6.52	63.66	29.82
Arts, entertainment, and recreation	18.83	67.92	13.24
Administrative and support service	29.98	70.02	0.00
Financial and insurance activities	0.00	71.28	28.72
Mining and quarrying	15.60	72.10	12.30
Activities of extraterritorial organizations	0.00	100.00	0.00

Source: Authors' compilation from the Zambia SWTS 2014.

At the provincial level, Muchinga Province recorded the highest number of mismatched youth, followed by the Southern Province. The low matching in Muchinga Province may be because it was a new province created in 2011 by separating it from the Northern Province. On the other hand, the Northwestern Province had the highest percentage of matched youth followed by Copperbelt Province. These two regions have a large mining economy, which attracts youth. Our results showed that the percentage of youth matched for their respective jobs in three provinces (Muchinga, Southern, and Lusaka province) was below the national weighted percentage. The low level of matching in Lusaka province, which is the capital province, was largely attributable to the fact that the youth often relocate to Lusaka and tend to take up un-matched jobs while they seek and await better opportunities.

In terms of the industry-specific matching, public administration and defense had the lowest-matched youth while those working in extraterritorial industries all reported that they were matched for their positions. Other notable industries in which more than 70% of youth reported being matched were administrative and support service, financial and insurance, and mining and quarrying. The higher percentage of matched youth among administrative and support services and financial and insurance could be attributed to market demand for specific skills sets. For mining and quarrying, mismatching could be explained by the fact that most positions for youth require a primary level of education and rely more on experience obtained from doing casual work.

Additionally, industries that relied more on unskilled labor (e.g., mining) were more likely to have matched individuals; this was similar for industries that relied on highly skilled labor. Less matching was expected for industries that employed a mix of highly skilled and unskilled labor or employed individuals with intermediate skill levels: both education and experience.

Of the 2,100 individuals who had completed their secondary or tertiary education, 16.4% reported having worked while studying. A comparison of the background characteristics of students with experience in working while studying and those who had never worked while studying revealed no statistically significant differences (Table 3A). Young men were more likely to work while studying than women, however. .

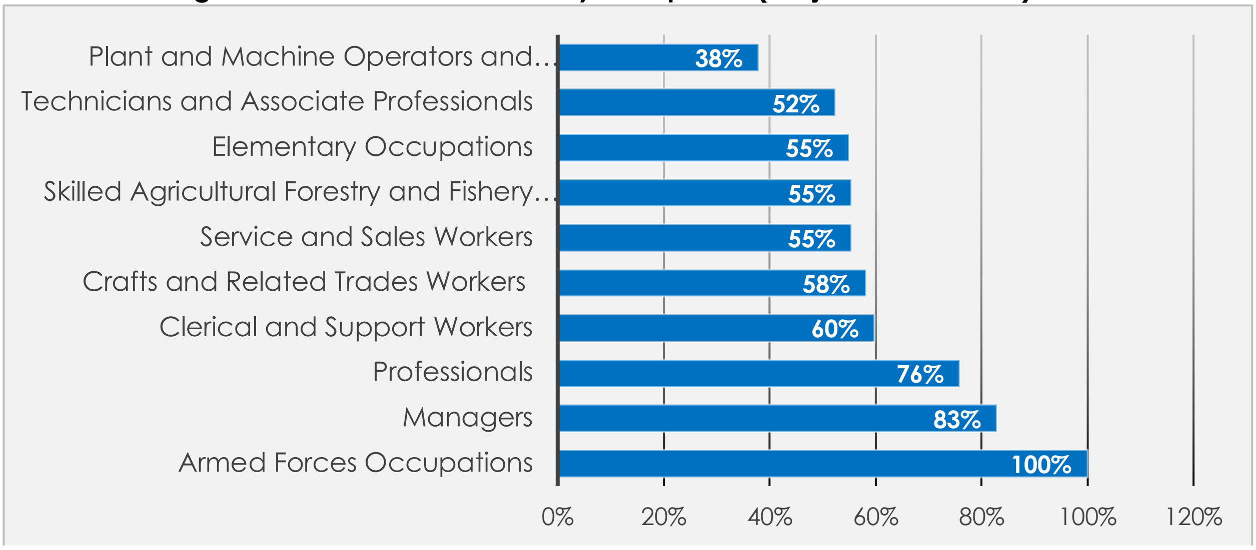
Additionally, descriptive statistics showed that individuals who worked while studying were less likely to be unemployed, suggesting that working while studying may have smoothed their integration into the labor market. Further, individuals who were married and held a college certificate/diploma and who were from rural areas were more likely to work while studying. Furthermore, the occupation of the father was more likely to affect an individual's decision to work while studying. That is, individuals whose parents' profession was in the agriculture sector or craft and related trade workers were more likely to work while studying; conversely, those with parents who were professionals, technicians, or associates were less likely to work while studying. This seems to suggest that youth who worked while studying were predominately from lower socioeconomic statuses.

Additionally, the results showed that matching was highest among youth in the armed forces followed by those in managerial and professional positions; plant and machine operators and assemblers had the lowest matching (Figure 5).

These findings show that professional occupations (e.g., scientists, health professionals, legal professionals) required specialized skills and a minimum level of education, which increased the likelihood that individuals would be matched for their positions.

Management occupations and the positions in the armed forces are usually based on experience, appointment, or promotion. A possible reason for higher undereducation among plant and machine operators and assemblers was that these occupations may have relied more on experience and physical strength than education (Kleibrink, 2013; Sicherman & Galor, 1990), which youth may not have acquired.

Figure 5: Matched individuals by occupation (subjective measure)



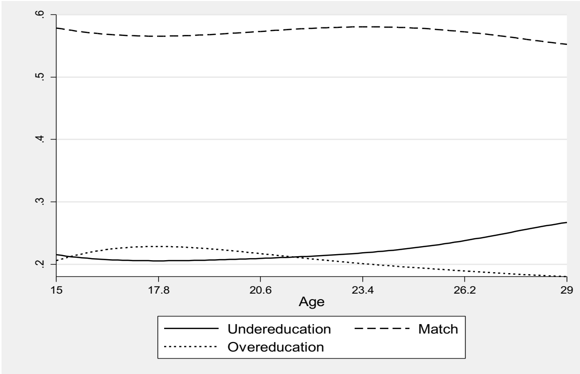
Source: Authors' compilation from the Zambia SWTS 2014.

Figure 6 below shows a panel of four figures. Panel (A) shows that matching of youth was not influenced by age, whereas the probability of a youth being overeducated for a given job decreased with age, and the probability of being undereducated increased with age. This finding could be attributed to the imperfect information in the labor market and the fact that workers at the beginning of their careers might settle for relatively low-skilled jobs to gain work experience. Their expectation that they could engage in on-the-job search while in a position for which they were overqualified may also explain this result (Brunello & Wruuck, 2019). However, in the years after graduation, they would acquired skills and experience, which would help them to take up positions that required more practical experience than educational qualifications.

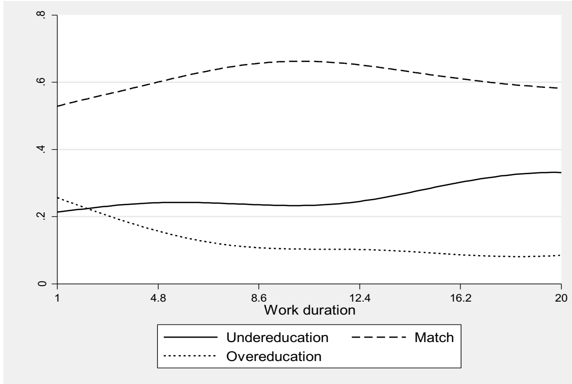
The results from Panel B show that matching improves with work duration. Increased exposure to the labor market increased the likelihood of finding a more suitable job, and this prompted youth to take up initial jobs for which they were not matched (Panel A). The result is the downward trend in the overeducated graph. Panel C shows that students with experience working while studying were more likely to be matched than their counterparts. This can be explained by the fact that youth who worked while studying were more likely to gain exposure and the skills necessary to take up jobs for which they were better matched.

Figure 6: Education Matching by Age, Work, and Duration

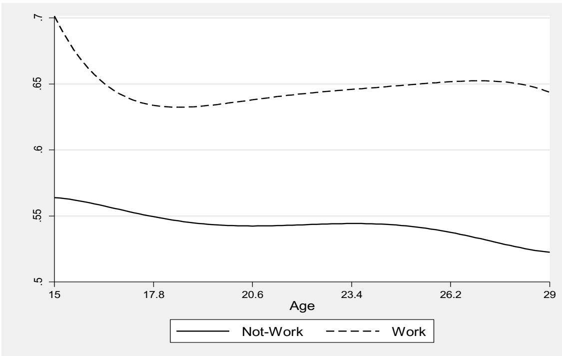
Panel (a): Education Matching and Age

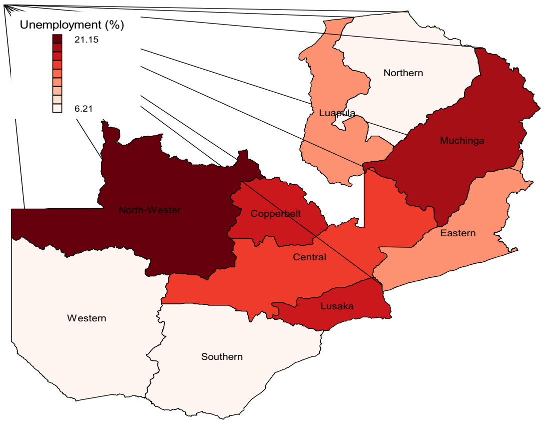


Panel (b): Education Matching and Work Duration



Panel (c): Education Matching, Working while Studying, and Age





Source: Authors' compilation from the Zambia SWTS 2014.

4.2 Main Estimation Results

4.2.1 Subjective Measure

Table 2 shows the results of the standard ordered probit (Column 1), extended ordered probit correcting for selection bias only (Column 2), and those correcting for selection and endogeneity bias (Column 3). Column 4 shows the results of the extended ordered probit, correcting for both selection bias and endogeneity bias and includes an artificial instrument. All regressions include a set of controls and specified instruments. The full model regression results are presented in Appendix Table A3.

In general, our results indicated that working while studying increased the likelihood of being overeducated compared to being undereducated or matched. The positive and significant correlation of the error terms of the selection and the mismatch equations (Column 4) confirms the presence of selection bias in the model. The results suggest that the unobservable characteristics that increased the chances of being employed also increased chances of being overeducated compared to being undereducated or matched. The correlations between the errors from the working while studying and mismatch equations were statistically insignificant, however (Column 4), which does not support the hypothesis that working while studying was an endogenous variable in the subjective model. As a result, we focused on the findings from the subjective model that corrected for selection bias only.

Table 2: Working While Studying and Educational Mismatching (Subjective)

Dependent Variable: Educational Mismatching (Subjective)	**Ordered Probit (1)**	**Extended Ordered Probit correcting for Selection Bias (2)**	**Extended Ordered Probit with correction for Selection Bias and Endogeneity Bias (3)**	**Extended Ordered Probit with correction for Selection Bias and Endogeneity Bias + Artificial Instrument (4)**
Working while Studying	0.205**	0.213**	0.199	0.180*
	(0.0867)	(0.0839)	(2.3227)	(0.099)
corr(e.select1,e.mismatch_subj)		0.471**	0.456**	0.450**
corr(e.work_study,e.mismatch_subj)			0.023	0.032
corr(e.work_study,e.select1)			0.133	-0.285**
Constant		0.814	0.813	1.054
		(0.9828)	(0.9894)	(0.976)
Observations	1224	1505	1505	1496
Pseudo R^2	0.033			
Selected	-	1224	1224	1224
Not Selected	-	281	281	281

Standard errors in parentheses.
Source: Authors' compilation from SWTS-Zambia 2014 data. Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results in Column 2 (Table 2) show a positive significant effect of working while studying on educational mismatching, after controlling for selection bias. That is, youth who worked while studying were more likely to be overeducated for their jobs vs. being undereducated or matched. From the results shown in Columns 1-4 in Table 2, we observed that the coefficient of working while studying decreased from 0.205 to 0.180 after accounting for selection and endogeneity biases. Column 3 shows that including empirical instruments without supplementing them with the constructed artificial instrument led to an insignificant finding, partly because the empirical instruments were weak. The cut points between the undereducated and matched categories for the ordered probit model were not statistically significant, which suggests that the two categories can be combined. We therefore estimated a probit model defining overeducated and undereducated individuals as 'unmatched' and the matched category remained intact (appendix Table A5). However, the results from the extended probit model show that working while studying was not significantly associated with educational mismatching.

Table 3 reports the average marginal effects for the subjective regression models presented in Table 2. The results from the subjective model, which corrects for selection only, show that working while studying reduced the likelihood or 'feeling' of being undereducated by approximately 7% and increased the likelihood or 'feeling' of being matched and overeducated by 2% and 5% respectively. However, although the results from the subjective model, which corrected for selection and endogeneity and included an artificial instrument, were statistically significant, they have the opposite signs. This difference could be attributed to the fact that no endogeneity between working while studying and mismatching was detected in the subjective model (Table 2).

Table 3: Working While Studying and Educational Mismatching (Subjective): Average Marginal Effects

	Oprobit Undereducated (1)	Matched (2)	Overeducated (3)
Coefficients	-0.064**	0.009*	0.055**
Observations	1224	1224	1224
	Extended Oprobit with Selection Bias Correction		
	Undereducated	*Matched*	*Overeducated*
Coefficients	-0.072**	0.019**	0.052**
Observations	1505	1505	1505
	Extended Oprobit with Selection Bias and Endogeneity Bias Correction + Artificial Instrument		
	Undereducated	*Matched*	*Overeducated*
Coefficients	0.109***	-0.037**	-0.071***
Observations	1496	1496	1496

Source: Authors' compilation from SWTS-Zambia 2014 data.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2.2 Empirical Measures

Table 4 shows the results based on our empirical specification of educational mismatching. The full regression results, including the controls and instruments, are presented in Appendix Table A4. Given that the empirical educational-mismatching measure was generated using the variable denoting the highest level of education of the respondent, we did not include respondents' education as a control variable to avoid perfect collinearity. Column 1 shows the results of the standard ordered probit regression model. Column 2 shows the results of the extended ordered probit model, which corrects for selection bias whereas Column 3 shows the results with corrections for both selection bias and endogeneity bias and Column 4 includes the artificial instrument.

Table 4: Working While Studying and Educational Mismatching (Empirical)

Dependent Variable: Educational Mismatching (Empirical)	Ordered Probit (1)	Extended Ordered Probit correcting for Selection Bias (2)	Extended Ordered Probit with correction for Selection Bias and Endogeneity Bias (3)	Extended Ordered Probit with correction for Selection Bias and Endogeneity Bias + Artificial Instrument (4)
Working while Studying	**0.319***** (0.0932)	**0.250***** (0.0878)	**-0.582***** (0.0754)	**0.209**** (0.094)
corr(e.select1,e.mismatch_emp)		-0.419	-0.326	-0.896***
corr(e.work_study,e.mismatch_emp)			0.485	0.202**
corr(e.work_study,e.select1)			0.118	-0.190
Constant		0.466 (1.0522)	-0.543 (0.9166)	-4.049*** (1.7110)
Observations	1102	1342	1342	1338
Pseudo R^2	0.128			
Selected	-	1102	1102	1099
Not Selected	-	240	240	239

Source: Compiled from the SWTS-Zambia 2014 Data, Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The results from the empirical model show that youth who worked while studying were more likely to be overeducated rather than being undereducated or matched for their job. The negative and significant correlation of the error terms of the selection and the mismatch equations (Column 4) confirms the presence of selection bias in the model. The results suggest that the unobservable characteristics that increase the chances of being employed reduce the chances of being overeducated compared to being undereducated or matched. Similarly, the correlation between the errors from the working while studying regressions and the mismatch regression was statistically significant (Column 4) , which implies that the unobservable factors that increase the chance of working while studying also increase the chances of being overeducated versus being undereducated or matched for the job.

The marginal effects from empirical model are presented in Table 5. Generally, working while studying increased the likelihood of being overeducated for the job, versus being undereducated or matched. The marginal effects from the model that corrects for endogeneity and selection bias shows that working while studying reduced the likelihood of being undereducated by 12%, reduced the likelihood of being matched by 12% and increased the likelihood of being overeducated by 24%.

Table 5: Working While Studying and Educational Mismatching (Empirical): Average Marginal Effects

	Oprobit Undereducated (1)	Matched (2)	Overeducated (3)
Coefficients	-0.065***	0.007	0.058***
Observations	1102	1102	1102
	Extended Oprobit with Selection Bias Correction		
	Undereducated	Matched	Overeducated
Coefficients	-0.0453***	-0.0180***	0.0633***
Observations	1342	1342	1342
	Extended Oprobit with Selection Bias and Endogeneity Bias Correction + Artificial Instrument		
	Undereducated	Matched	Overeducated
Coefficients	-0.117***	-0.121***	0.238***
Observations	1496	1496	1496

Source: Authors' compilation from SWTS-Zambia 2014 data.
** $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

4.2.3 Instrument Tests

We tested the strength of the specified instruments using estimates from the univariate IV-probit regressions of the main regression equation. Table 6 reports the results of diagnostic tests from the first-stage regressions of the IV-probit estimations. We used the STATA command *'rivtest'* to test the over-identification restriction and the strength of our instruments. The null hypothesis of the rivtest states that the set of instruments are weak instruments (Stock, Yogo & Wright, 2002).

The results indicated that the joint test of the instruments' relevance (F-tests) was significant for both the empirical measure and the subjective measure. In both specifications, the F-statistic of joint significance of the instruments exceeds 10, the threshold recommended by Staiger and Stock (1994), which implies that the instruments were relevant.

For the subjective measure, we found that the problem of weak instruments was not present in estimations using the Conditional Likelihood Ratio test (Moreira's CLR; (Moreira, 2003), which is the most restrictive. We also considered the Anderson-Rubin (AR) test, which is a joint test of the structural parameter and the over-identification restrictions. For the empirical measure, on the other hand, we found that we cannot reject the null hypothesis that our instruments were weak instruments.

Table 6: Instrument Tests with rivtest and ivreg2 Commands

	Subjective Measure of Endogeneity	Empirical Measure IV
ivprobit-Rivtest	**P-value**	**P-value**
CLR	0.0232	0.0697
AR	0.0618	0.7133
Wald	0.0230	0.0696
F-Statistic	142.05	219.43
ivreg2-PE Tests		
LM	0.0000	0.0000
CD Wald F stat	331.979	848.014
Sargan	0.0442	0.0000

Source: Authors' compilation from SWTS-Zambia 2014 data.

We also tested the instruments using the post-estimation tests of the "ivreg2" command in Stata. Just as the ivprobit regression case, we found that for the both subjective and empirical measures, we cannot reject the null hypothesis that the instruments may be over-identified. The test does, however, indicate the absence of under-identification. Additionally, the Cragg-Donald (CD) F statistic for both the subjective and empirical measure was significantly larger than ten, indicating that our instruments were jointly highly correlated with working while studying. Based on the results of these two tests we conclude that our instruments may be considered weak instruments.

V. Conclusions and Policy Implications

We set out to determine the causal effect of working while studying on educational mismatching among youth in Zambia using two complementary approaches. For both the empirical and subjective approaches, we found that youth who worked while studying had a lower probability of being or "feeling" undereducated and a higher probability of being or "feeling" overeducated for their jobs. However, working while studying had opposite effects on being matched for jobs using the empirical and subjective approach. In essence, working while studying reduced the likelihood of being matched for the job using the empirical measure and increased the likelihood or "feeling" being matched using the subjective approach.

The results from the empirical model, which showed that working while studying reduced the likelihood of being matched, could be explained by the career-transition theory, according to which new entrants into the labor market accept lower positions in their preferred firms with the hope of acquiring a better-suited position later on. Workers at the beginning of their career might settle for relatively low-skilled jobs to gain work experience. In fact, accepting lower-level jobs with low risks of adaptation and reduced job search, such as short-term or part-time jobs, might not be as problematic as being unemployed for extended periods (Baert & Verhaest, 2019). Continuing to work at the job one held while a student, even at the time of graduation, may generate locking-in effects, which, in turn, lead to worker dissatisfaction and lower productivity. In some developed country contexts, low-quality employment has been shown to be more damaging than unemployment, while, in others, skill underutilization has been less detrimental than unemployment.

Furthermore, the finding from the empirical model that youth who worked while studying were less likely to be matched for their jobs could be attributed to the negative influence of working while studying on educational attainment, similar to Jewell's report (2014). Working while studying could interfere with schooling, resulting in reduced academic achievement and a lower quality degree. The literature has also suggested that combining education with work may, for instance, signal lower social background and a lack of in educational development (Verhaest et al., 2016). In fact, most of the youth who worked while studying in the survey were from the households of lower socioeconomic status. Carnevale et al. (2015) argued that work done while studying in fields unrelated to the study area interferes with educational attainment and becomes counterproductive.

Theoretically, we expected youth who worked while to be less likely to be overeducated for their job. The literature has reported that, for a given level of education, being overeducated for a job leads to lower job satisfaction, lower life satisfaction, more depressive symptoms, more turnover, etc. The result that working while studying leads to youth being overeducated for their jobs suggests that youth get lower wages for their level of education; if we assumed that productivity was equal to wages, then there was a loss in productivity as well (Brunello & Wruuck, 2019). However, it has been also argued that the overeducated are just as productive as those who are matched or undereducated and that the discrepancy in wages is a result of excess supply for the job (Brunello & Wruuck, 2019). In fact, undereducation is not unambiguously negative because it may lead to higher earnings and be associated with challenging jobs that offer significant learning opportunities. Our study showed that those who combine work while studying do not end up with less prestigious jobs than their equally qualified counterparts that did not combine their education with work.

Baert and Verhaest (2019) found that unemployment was a worse signal than overeducation because it was perceived to be sign of lower motivation. It also implied that youth engaged in some work were in a better position to get a well-matched job than those who were unemployed. To the extent that mismatching may be the result of asymmetric information among job seekers, workers, and firms, improvement in career guidance and counselling has been recommended (McGuiness et al., 2017).

This study has limitations. Measures that rely on self-reported mismatching suffer from measurement error because respondents tend to overstate the needs of their jobs and the status of their position (Hartog, 2000). As a result of the nature of our data, individuals who were still in school were excluded from the analysis, and this presents another potential source of selection bias. Our study was unable to disentangle the effects of different types of working while studying (internships, e.g.) on mismatching because of insufficient data points: only 5% of youth reported doing an internship. It is clear from the literature that effects differ depending upon whether students are engaged in regular work experience or other work types that are combined with internships and apprenticeships as part of training. Future studies should investigate the effects of the specific type of work performed while studying on educational mismatching in the context of developing countries.

In summary, our results show that working while studying reduced the likelihood of being undereducated for the position but increased the likelihood of being overeducated. Our results imply that additional support to enable youth to get appropriate exposure to work during their college or university studies could potentially increase productivity by ensuring that they are well-matched for their jobs. Currently, stakeholders in Zambia are designing work-based skills development programs. There is, therefore, a need to consider the possible counter effects of combining learning and working. Furthermore, there is a need to invest in guidance mechanisms for students who wish to combine work and learning.

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Appendix

Table A1: Description of the variables

Variable	Description
Employment Status	Dummy variable coded as 1 if the individual was employed and 0 otherwise.
Educational Mismatching for employed youth	Variable coded as 0, undereducated, if the actual educational level was below the modal education category for the occupation based on the ISCO classification; coded as 1 if the education level was an exact match; and coded as 3 if the education level was higher than the modal education level in the ISCO occupational category.
Gender	Dummy variable coded as 1 if the young person was a man, 0 otherwise.
age: 15-19	Dummy variable coded as 1 if the individual was between 15-19 years of age, 0 otherwise.
age: 20-24	Dummy variable coded as 1 if the individual was between 20-24 years of age, 0 otherwise.
age: 25-29	Dummy variable coded as 1 if the individual was aged between 25-29 years of age, 0 otherwise.
Married	Dummy variable coded as 1 if the individual was married, 0 otherwise.
Youth Education	
Primary	Dummy variable coded as 1 if the individual was attending primary school, 0 otherwise.
Secondary	Dummy variable coded as 1 if the individual was attending secondary school or other skills training, 0 otherwise.
Tertiary	Dummy variable coded as 1 if the individual was attending tertiary school, 0 otherwise.
Parents Education	Continuous variable denoting the highest level of education for both parents.
Household Financial Situation	Dummy variable coded as 1 if respondent came from a household that was reported to be poor or fairly poor.
Region	Variable denoting the ten regions in the country: Central, Copperbelt, Eastern, Luapula, Lusaka, Muchinga, Northwestern, Northern, Southern, and Western. Lusaka province was the reference category.
Migrate	Dummy variable coded as 1 if the individual migrated and 0 otherwise.
Rural	Dummy variable coded as 1 if the individual resided in a rural area and 0 otherwise.
Instruments	
Young children	Number of children the respondent had.
Environment	Continuous variable ranging from 0 to 1 indicating the poverty status of the neighborhood in which the young person resided.
Internship	1 if internship with an employer was a mandatory part of the young person's education and 0 otherwise.
Variable of interest	
Working while Studying	1 if the youth worked while studying in college or university, 0 otherwise.

Table A2: Background Characteristics of respondents by Working while Studying

	Overall Sample	Work while studying	Not working while studying	
Number of Observations	**1,800**	**295**	**1505**	**t-test**
Proportion		0.1639	0.8361	
Variables	**Mean**	**Mean**	**Mean**	
Men	53.22	73.55	49.235	7.78***
Unemployed	13.33	8.47	14.29	-2.69***
By Education (%)				
Primary	31.33	27.46	32.09	-1.57
Skills training	0.89	1.02	0.09	0.26
Secondary School	61.22	61.02	61.26	-0.08
College Certificate/Diploma	4.67	8.81	3.85	3.71***
University	`1.89	1.69	1.93	-0.28
Other variable				
Married	28.44	33.56	27.44	2.13***
Have a child (yes=1)	43.89	44.41	43.79	0.20
Migrants	25.39	28.81	24.72	1.48*
Rural	54.89	60.00	53.89	1.93**
Father's education (%)				
Primary	45.78	44.41	46.05	0.52
Skills training	1.44	2.71	1.20	2.00**
Secondary School	33.17	33.22	33.16	0.02
College Certificate/Diploma	12.78	13.22	12.69	0.25
University	6.83	6.44	6.91	0.29
Mother's education (%)				
Primary	51.50	51.19	51.56	-0.12
Skills training	0.56	0.68	0.53	0.31
Secondary School	25.50	29.83	24.65	1.87**
College Certificate/Diploma	6.44	4.75	6.78	-1.30
University	16.00	13.56	16.48	-1.25
Father's Profession (%)				
managers	2.83	2.71	2.86	-0.14
professionals	13.83	12.20	14.15	-0.89
technicians and associate professionals	2.78	1.02	3.12	-2.01**
clerical support workers	1.78	2.03	1.73	0.36
service and sales workers	9.67	8.81	9.83	-0.54
skilled agricultural, forestry and fish	15.56	18.98	14.88	1.78**
craft and related trades workers	9.50	15.25	8.37	3.70***
plant & machine operators, and assembly	6.83	7.46	6.71	0.46
elementary occupations	9.56	8.81	9.70	-0.47
armed forces occupations	3.22	4.75	2.92	1.62*

Table A3: Working while Studying and Educational Mismatching: Subjective Measure

	M1 OPROBIT	M2 OPROBIT|SB_CORR		M3 OPROBIT|SB_CORR |EN_CORR			M4 OPROBIT|SB_CORR|EN_CORR |ARTF_IV		
	mismatch	mismatch	select1	mismatch	select1	work/study	mismatch	select1	work/study
Working while Studying	**0.205** (0.087)**	**0.213** (0.084)**		**0.199 (2.323)**			**0.180* (0.099)**		
Individual characteristics:									
Log of Age	0.357 (0.233)	0.378* (0.229)	0.363 (0.307)	0.376 (0.349)	0.357 (0.308)	-0.516 (0.330)	0.355 (0.229)	0.314 (0.304)	-0.231 (0.542)
Men	-0.036 (0.071)	-0.012 (0.071)	0.109 (0.092)	-0.011 (0.303)	0.108 (0.092)	0.548*** (0.130)	-0.009 (0.071)	0.126 (0.091)	0.124 (0.145)
Number of children	-0.022 (0.037)	-0.024 (0.037)	-0.056 (0.051)	-0.023 (0.045)	-0.054 (0.052)	-0.021 (0.157)	-0.022 (0.037)	-0.041 (0.051)	0.025 (0.237)
Living in rural area	-0.054 (0.078)	-0.000 (0.081)	0.013 (0.110)	-0.002 (0.091)	0.014 (0.110)	0.032 (0.112)	0.001 (0.081)	0.029 (0.111)	0.141 (0.158)
Migrant	0.138* (0.075)	0.151** (0.074)	0.067 (0.099)	0.151* (0.079)	0.063 (0.099)	0.076 (0.123)	0.151** (0.074)	0.066 (0.099)	0.173 (0.146)
Marital status:									
--Engaged To Be Married	-0.227 (0.171)	-0.178 (0.168)	0.280 (0.294)	-0.178 (0.301)	0.307 (0.297)	0.391* (0.227)	-0.178 (0.169)	0.264 (0.296)	-0.093 (0.281)
--Married	-0.218** (0.091)	-0.197** (0.090)	0.141 (0.124)	-0.197 (0.136)	0.140 (0.125)	0.166 (0.129)	-0.196** (0.090)	0.142 (0.126)	0.081 (0.196)
--Separated/Divorced	-0.417** (0.177)	-0.381** (0.176)	0.014 (0.254)	-0.382** (0.176)	0.011 (0.252)	0.029 (0.333)	-0.381** (0.176)	-0.007 (0.255)	0.046 (0.483)
--Widowed	0.016 (0.366)	0.021 (0.369)	0.214 (0.734)	0.022 (0.372)	0.204 (0.730)	-4.309*** (0.263)	0.000 (.)	0.000 (.)	0.000 (.)

--Skills Training Center	0.170 (0.576)	0.118 (0.561)	-0.436 (0.399)	0.124 (0.672)	-0.444 (0.401)	1.260** (0.512)	0.137 (0.559)	-0.390 (0.394)	0.084 (0.779)
--Secondary School	-0.062 (0.104)	-0.084 (0.103)	-0.340** (0.170)	-0.080 (0.516)	-0.333* (0.171)	1.585*** (0.264)	-0.065 (0.105)	-0.318* (0.170)	0.412** (0.206)
--College Certificate / Diploma	0.446** (0.177)	0.414** (0.176)	-0.417 (0.265)	0.420 (0.841)	-0.421 (0.264)	2.072*** (0.340)	0.438** (0.176)	-0.389 (0.264)	0.467 (0.348)
--University	-0.188 (0.232)	-0.302 (0.232)	-0.821*** (0.298)	-0.294 (0.555)	-0.813*** (0.300)	1.691*** (0.427)	-0.279 (0.233)	-0.800*** (0.296)	0.599 (0.557)
--Post-Graduate Studies	4.963*** (0.276)	5.467*** (0.600)	-0.905 (0.729)	5.305*** (0.692)	-0.905 (0.733)	-3.096*** (0.467)	0.000 (.)	0.000 (.)	0.000 (.)
Work Duration	-0.020** (0.009)	-0.014 (0.009)	0.065*** (0.017)	-0.015 (0.033)	0.064*** (0.017)	-0.057*** (0.012	-0.014 (0.009)	0.063*** (0.017)	0.012 (0.021)
cut1	-0.044 (0.707)								
cut2	1.496** (0.708)								
corr(e.select1,e.mismatch_subj)		0.471** (0.199)		0.456** (0.206)			0.450** (0.205)		
corr(e.work_study,e.mismatch_subj)				0.023 (1.351)			0.032 (0.104)		
corr(e.work_study,e.select1)				0.133 (0.088)			-0.285** (0.117)		
Controls for Selection Bias:									
Unemployment rate by Ward			-5.737*** (0.568)		-5.716*** (0.562)			-5.717*** (0.562)	
Number of children squared						0.021 (0.044)			-0.009 (0.066)
Artificial Instrument									4.591*** (0.221)
Constant term:									

Constant			0.914 (0.983)		0.929 (0.986)			1.054 (0.976)	
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mother's occupation	No	No	Yes	No	Yes	No	No	Yes	No
Father's education	No	No	No	No	No	Yes	No	No	Yes
Father's occupation	No	No	No	No	No	Yes	No	No	Yes
Observations	1224	1505		1505			1496		
Pseudo R^2	0.033								
Pseudo R_Squares									

Standard errors in parentheses.
Source: Produced by the authors using SWTS-Zambia 2014 data.
* p < 0.1, ** p < 0.05, *** p < 0.01

Table A4: Working while Studying and Educational Mismatching: Empirical Measure

	M1	M2		M3			M4		
	OPROBIT	**OPROBIT|SB_CORR**		**OPROBIT|SB_CORR|EN_CORR**			**OPROBIT|SB_CORR|EN_CORR|ARTF_IV**		
	mismatch	**mismatch**	**select1**	**mismatch**	**select1**	**work/study**	**mismatch**	**select1**	**work/study**
Working while Studying	**0.319*** (0.093)**	**0.250*** (0.088)**		**-0.582*** (0.075)**			**0.209** (0.094)**		
Individual characteristics:									
Log of Age	3.602*** (0.311)	3.232*** (0.307)	0.576* (0.308)	3.031*** (0.282)	0.569* (0.293)	-0.286 (0.297)	3.241*** (0.309)	0.515* (0.313)	-0.220 (0.576)
Male	0.104 (0.084)	0.033 (0.078)	0.227** (0.101)	0.154** (0.076)	0.227** (0.095)	0.531*** (0.096)	0.039 (0.078)	0.236** (0.101)	0.138 (0.198)
Number of children	-0.287*** (0.049)	-0.263*** (0.045)	0.013 (0.055)	-0.249*** (0.044)	0.010 (0.054)	-0.083 (0.119)	-0.268*** (0.046)	0.027 (0.055)	0.074 (0.264)
Living in rural area	-0.035 (0.100)	-0.124 (0.095)	0.216 (0.137)	-0.114 (0.090)	0.211 (0.131)	0.017 (0.101)	-0.129 (0.095)	0.232* (0.139)	-0.488*** (0.185)
Migrant	-0.041 (0.085)	-0.061 (0.080)	0.042 (0.101)	-0.039 (0.078)	0.043 (0.100)	0.129 (0.094)	-0.055 (0.080)	0.038 (0.102)	0.038 (0.181)
Marital status:									
--Engaged To Be Married	-0.372* (0.221)	-0.422** (0.194)	0.446 (0.314)	-0.300* (0.173)	0.437 (0.315)	0.373* (0.190)	-0.413** (0.193)	0.436 (0.313)	-0.079 (0.619)
--Married	-0.310*** (0.114)	-0.303*** (0.104)	0.186 (0.127)	-0.257** (0.102)	0.177 (0.124)	0.094 (0.124)	-0.296*** (0.105)	0.180 (0.129)	0.077 (0.232)
--Separated/Divorced	-0.297 (0.221)	-0.355* (0.204)	-0.158 (0.235)	-0.356* (0.200)	-0.164 (0.233)	-0.103 (0.255)	-0.345* (0.205)	-0.170 (0.238)	-0.047 (0.324)
--Widowed	-1.511** (0.727)	-1.252* (0.663)	0.086 (0.759)	-1.268* (0.670)	0.082 (0.754)	-7.635*** (0.307)	0.000 (.)	0.000 (.)	0.000 (.)
Work Duration	-0.055*** (0.014)	-0.058*** (0.013)	0.069*** (0.017)	-0.040*** (0.013)	0.068*** (0.017)	0.061*** (0.012)	-0.058*** (0.013)	0.070*** (0.017)	0.013 (0.025)
cut1	9.712*** (0.927)								

cut2	12.211*** (0.957)								
corr(e.select1,e.mismatch_emp)		-0.904*** (0.100)		-0.845 (.)			-0.896*** (0.111)		
corr(e.work_study,e.mismatch_emp)				0.452 (.)			0.202** (0.099)		
corr(e.work_study,e.select1)				0.095 (.)			-0.190 (0.162)		
Controls for Selection Bias:									
Unemployment rate by Ward			-6.690*** (0.961)		-6.590*** (0.564)			-6.729*** (0.992)	
Instruments for Work/Study									
Number of children squared						0.032 (0.033)			-0.035 (0.074)
Artificial Instrument									6.019*** (0.433)
Constant term:									
Constant			-0.052 (1.052)		-0.038 (0.969)			0.125 (1.072)	
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mother's occupation	No	No	Yes	No	Yes	No	No	Yes	No
Father's education	No	No	No	No	No	Yes	No	No	Yes
Father's occupation	No	No	No	No	No	Yes	No	No	Yes
Observations	1102	1342		1342			1338		
Pseudo R^2	0.128								
Pseudo R_Squares									

Standard errors in parentheses.
Source: Produced by the authors using SWTS-Zambia 2014 data.

Table A5: Working while Studying and Educational Mismatching (Subjective Probit)

<table>
<tr><th></th><th>M1 PROBIT</th><th>M2 PROBIT|SB_CORR</th><th>M3 PROBIT|SB_CORR|EN_CORR</th><th>M4 PROBIT|SB_CORR|EN_CORR|ARTF_IV</th></tr>
</table>

	mismatch	mismatch	select1	mismatch	select1	work/study	mismatch	select1	work/study
Working while Studying	**0.109**	**0.114**		**-1.009****			**-0.096**		
Individual characteristics:									
Log of Age	0.238	0.254	0.334	0.095	0.324	-0.475	0.245	0.257	0.101
Male	0.040	0.050	0.126	0.192*	0.127	0.496***	0.074	0.138	0.016
Number of children	-0.044	-0.045	-0.039	-0.029	-0.036	-0.059	-0.044	-0.025	-0.025
Living in rural area	-0.199**	-0.172*	0.016	-0.132	0.019	0.053	-0.160*	0.027	-0.050
Migrant	0.061	0.069	0.075	0.077	0.072	0.085	0.066	0.070	0.046
Marital status:									
- Engaged To Be Married	0.163	0.184	0.272	0.283	0.298	0.348	0.206	0.270	-0.466
- Married	0.090	0.097	0.137	0.140	0.137	0.134	0.114	0.140	-0.112
- Separated/Divorced	-0.035	-0.023	-0.015	-0.016	-0.013	0.000	-0.032	-0.024	0.090
- Widowed	0.413	0.410	0.132	0.419	0.127	-4.331***	0.000	0.000	0.000
Education level:									
--Primary Education	-0.062	-0.064	-0.139	0.108	-0.134	1.358***	-0.036	-0.129	0.290
--Skills Training Center	-1.170*	-1.178*	-0.389	-0.886	-0.375	1.362***	-1.146*	-0.365	0.004
--Secondary School	-0.174	-0.185	-0.296*	0.059	-0.285*	1.572***	-0.142	-0.281*	0.222
--College Certificate / Diploma	-0.023	-0.033	-0.341	0.345	-0.345	2.078***	0.042	-0.320	0.350
--University	0.623	0.564	-0.782***	0.731*	-0.771***	1.628***	0.623	-0.765***	-0.328
--Post-Graduate Studies	0.000	-5.955***	-0.834	-4.850***	-0.829	-3.146***	0.000	0.000	0.000
Work Duration	0.009	0.012	0.061***	0.027**	0.060***	0.064***	0.015	0.061***	0.017
Controls for Selection Bias:									
Unemployment rate by Ward			-5.873***		-5.832***			-5.827***	
Instruments for work/study									
Number of children squared						0.027			-0.012
Artificial Instrument									4.895***
Correlations									
corr(e.work_study,e.mismatch_subj)						0.665***			0.491***
corr(e.work_study,e.select1)						0.146**			-0.068
corr(e.select1,e.mismatch_subj)			0.230		0.243			0.233	
Constant term:									
Constant	-0.339	-0.481	1.060	-0.208	1.080	-1.582*	-0.479	1.259	-2.944

Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mother's occupation	No	No	Yes	No	Yes	No	No	Yes	No
Father's education	No	No	No	No	No	Yes	No	No	Yes
Father's occupation	No	No	No	No	No	Yes	No	No	Yes
Observations	1223	1505		1505			1496		
Pseudo R^2	0.023								

Source: Produced by the authors using SWTS-Zambia 2014 data.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Working while Studying and Educational Mismatching (Empirical Probit)

	M1 OPROBIT	M2 OPROBIT|SB_CORR		M3 OPROBIT|SB_CORR|EN_CORR			M4 OPROBIT|SB_CORR|EN_CORR|ARTF_IV		
	mismatch	mismatch	select1	mismatch	select1	Working Studying	mismatch	select1	Working Studying
Working while Studying	**0.077**	**0.077**		**-1.085***			**-0.088**		
Individual characteristics:									
Log of Age	-1.264***	-1.266***	0.387	-1.220***	0.369	-0.154	-1.282***	0.305	-0.003
Male	-0.071	-0.075	0.158	0.095	0.160	0.533***	-0.044	0.169*	0.221*
Number of children	-0.086*	-0.086*	-0.019	-0.074	-0.015	0.031	-0.086*	-0.001	-0.020
Living in rural area	0.155	0.151	0.131	0.142	0.128	-0.005	0.146	0.142	0.042
Migrant	-0.009	-0.010	0.039	0.018	0.035	0.130	-0.002	0.035	0.111
Marital status:									
--Engaged To Be Married	-0.152	-0.156	0.446	0.016	0.457	0.302	-0.130	0.420	-0.131
--Married	-0.052	-0.054	0.145	-0.004	0.145	0.113	-0.043	0.129	-0.008
--Separated/Divorced	0.139	0.136	0.005	0.096	0.013	-0.099	0.133	-0.025	0.136
--Widowed	-0.535	-0.530	0.222	-0.583	0.205	-5.146***	0.000	0.000	0.000
Work Duration	-0.002	-0.003	0.066***	0.019	0.064***	0.063***	0.000	0.067***	0.002
Controls for Selection Bias:									
Unemployment rate by Ward			-7.975***		-7.919***			-7.982***	
Instruments for work/study									
Number of children squared						-0.009			-0.003
Artificial Instrument									4.896***
Correlations									
corr(e.work_study,e.mismatch_emp)						0.663*			0.390***
corr(e.work_study,e.select1)						0.140*			-0.264**
corr(e.select1,e.mismatch_emp)			-0.039		0.036			0.007	
Constant term:									
Constant	4.522***	4.544***	0.708	4.346***	0.766	-1.227	4.583***	0.935	-2.423
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mother's occupation	No	No	Yes	No	Yes	No	No	Yes	No
Father's education	No	No	No	No	No	Yes	No	No	Yes
Father's occupation	No	No	No	No	No	Yes	No	No	Yes
Observations	1102	1342		1342			1338		
Pseudo R^2	0.045								
Pseudo R_Squares									

Source: Produced by the authors using SWTS-Zambia 2014 data.
* p < 0.1, ** p < 0.05, *** p < 0.01

Table A7: Working while Studying and Educational Mismatching (Empirical- Probit)with Work/Study in three categories

	M1 PROBIT	M2 PROBIT|SB_CORR		M3 PROBIT|SB_CORR|EN_CORR			M4 PROBIT|SB_CORR|EN_CORR|ARTF_IV		
	Mismatch	mismatch	select1	mismatch	select1	workstudy2	mismatch	select1	workstudy2
Did not work while studying	**0.000**	**0.000**		**0.000**			**0.000**		
Worked during holidays or did internship	**0.106**	**0.106**		**-0.476**			**0.165**		
Worked during school season	**0.057**	**0.056**		**-0.843**			**-0.101**		
Individual characteristics:									
Log of Age	-1.267***	-1.269***	0.388	-1.285***	0.370	-0.268	-1.286***	0.387	-0.057
Male	-0.072	-0.076	0.158	0.033	0.160	0.496***	-0.071	0.157	-0.124
Number of children	-0.086*	-0.087*	-0.019	-0.081*	-0.015	-0.007	-0.086*	-0.019	-0.119
Living in rural area	0.154	0.151	0.131	0.147	0.127	-0.014	0.148	0.136	0.010
Migrant	-0.010	-0.011	0.039	0.003	0.036	0.086	-0.013	0.043	0.047
Marital status:									
--Engaged To Be Married	-0.150	-0.155	0.446	-0.032	0.457	0.360*	-0.144	0.450	0.162
--Married	-0.051	-0.052	0.145	-0.008	0.145	0.177	-0.046	0.147	0.063
--Separated/Divorced	0.138	0.135	0.005	0.109	0.011	-0.049	0.122	0.001	-0.170
--Widowed	-0.536	-0.530	0.222	-0.572	0.207	-4.718***	-0.531	0.229	-3.482***
Working Duration	-0.002	-0.003	0.066***	0.013	0.065***	0.062***	-0.001	0.066***	0.003
Controls for Selection Bias:									
Unemployment rate by Ward			-7.975***		-7.912***			-7.978***	
Instruments for work/study									
Artificial Instrument									-5.444***
Number of Children Squared									0.014
Correlations									
cut1						0.745			-3.309**
cut2						1.125			-1.100
corr(e.workstudy2,e.mismatch_emp)						0.439			0.274***
corr(e.workstudy2,e.select1)						0.117			-0.276**
corr(e.select1,e.mismatch_emp)			-0.041		0.017			-0.095	
Constant term:									
Constant	4.531***	4.554***	0.706	4.576***	0.763		4.624***	0.709	
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mother's occupation	No	No	Yes	No	Yes	No	No	Yes	No
Father's education	No	No	No	No	No	Yes	No	No	Yes

Father's occupation	No	No	No	No	No	Yes	No	No	Yes
Observations	1102	1342		1342			1342		
Pseudo R^2	0.045								
Pseudo R_Squares									

Source: Produced by the authors using SWTS-Zambia 2014 data.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Working while Studying and Educational Mismatching (Subjective Probit) with Work/Study in Three Categories

	M1 PROBIT	M2 PROBIT|SB_CORR		M3 PROBIT|SB_CORR|EN_CORR			M4 PROBIT|SB_CORR|EN_CORR|ARTF_IV		
	mismatch	mismatch	select1	mismatch	select1	workstudy2	mismatch	select1	workstudy2
Did not work while studying	**0.000**	**0.000**		**0.000**			**0.000**		
Worked during holidays or did internship	**0.049**	**0.049**		**-0.388**			**0.170**		
Worked during school season	**0.217***	**0.215***		**-0.489**			**0.024**		
Individual characteristics:									
Log of Age	0.275	0.315	0.591*	0.194	0.567*	-0.649**	0.258	0.492	-0.535
men	0.061	0.104	0.187*	0.191	0.198*	0.543***	0.107	0.208**	-0.186
Number of children	-0.026	-0.027	-0.035	-0.018	-0.029	0.035	-0.025	-0.008	-0.095
Living in rural area	-0.207**	-0.145	0.121	-0.136	0.117	-0.000	-0.134	0.128	-0.019
Migrant	0.003	0.020	0.093	0.028	0.090	0.063	0.013	0.081	-0.152
Marital status:									
- Engaged to be married	0.365	0.412*	0.448	0.470*	0.483	0.268	0.401*	0.514	0.083
- Married	0.084	0.097	0.115	0.133	0.115	0.189	0.111	0.111	0.100
- Separated/divorced	0.056	0.086	-0.031	0.079	-0.035	0.015	0.076	-0.039	-0.174
Widowed	0.670	0.535	0.189	0.515	0.181	-4.751***	0.000	0.000	0.000
Education level:									
- Primary education	0.549*	0.495	-0.302	0.452	-0.330	-0.150	0.460	-0.291	-0.385
Skills training center	-0.563	-0.605	-0.555	-0.582	-0.563	-0.006	-0.600	-0.533	0.438
- Secondary school	0.441	0.363	-0.484	0.350	-0.509	0.046	0.333	-0.463	-0.371
- College certificate/diploma	0.608*	0.531	-0.559	0.597	-0.598	0.578	0.516	-0.516	-0.054
- University	1.231**	1.021**	-0.993*	0.995*	-1.010*	0.210	1.002**	-0.974*	-0.089
- Masters level or higher studies	0.000	-4.687***	-0.811	-5.101***	-0.833	-5.101***	0.000	0.000	0.000
Working duration	-0.006	-0.000	0.064***	0.011	0.062***	0.060***	0.002	0.065***	0.018

Controls for Selection Bias:									
Unemployment rate by Ward			- 7.947***		- 7.857***			-7.868***	
Instruments for Work/Study									
Artificial instrument									5.133***
Number of children squared									0.013
Correlations									
cut1						-0.475			0.027
cut2						-0.084			2.181
corr(e.workstudy2,e.mismatch_subj)						0.363			0.271**
corr(e.workstudy2,e.select1)						0.141*			-0.245*
corr(e.select1,e.mismatch_subj)			0.539***		0.571***			0.539***	
Constant term:									
Constant	-1.010	-1.308	0.385	-0.930	0.490		-1.104	0.608	
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mother’s occupation	No	No	Yes	No	Yes	No	No	Yes	No
Father’s education	No	No	No	No	No	Yes	No	No	Yes
Father’s occupation	No	No	No	No	No	Yes	No	No	Yes
Observations	1048	1289		1289			1283		
Pseudo R^2	0.032								
Pseudo R_Squares									

Source: Produced by the authors using SWTS-Zambia 2014 data.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$