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Do you really need it? Educational mismatch and earnings in Ghana

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Abstract
This study examines the effects of educational mismatch on earnings using cross-sectional data from three rounds of the Ghana Living Standards Survey. There are gender-earnings differentials, with women suffering a penalty for undereducation that is almost twice that paid by men for having less than the required years of education, although the premium associated with overeducation is higher for women. While the penalty associated with deficit schooling decreases for men over time, this penalty increases for women. Women but not men experience significant increases in returns for attaining the required education. On the contrary, the lack of significance of returns to overeducation over time suggests that human capital beyond the required level is unproductive and may represent a waste of public resources.

KEYWORDS
earnings, gender, human capital, overeducation, undereducation

JEL CLASSIFICATION
I26; J24; J31

1 | INTRODUCTION

This study examines the incidence and effects of educational mismatch on earnings in Ghana between 1998 and 2013. Previous research, mostly for developed countries, that has examined educational mismatches identifies costs associated with mismatch due to both overeducation and undereducation

(Groot & van den Brink, 2000a, 2000b; Kiker, Santos, & de Oliveira, 1997; McGuinness, 2006). While overeducated workers are generally found to be associated with higher earnings (Belfield, 2010; Hartog, 2000; Rubb, 2003), the rewards for required education, accrued to those who avoid mismatch, are higher (Daly, Büchel, & Duncan, 2000; Dolton & Vignoles, 2000; Kiker et al., 1997). There are also notable gender differences in the incidence of a mismatch, with women often constituting a lower proportion of those who are undereducated than men although the pattern varies by country (Cohn & Ng, 2000; Daly et al., 2000).[1]

However, evidence from developing countries is sparse although we know much about overall educational attainment and returns to schooling (Psacharopoulos & Patrinos, 2002). Among the few studies in this area are those of Mehta, Felipe, Quising, and Camingue (2011) and Quinn and Rubb (2006). Herrera and Merceron (2013) have also analyzed overeducation for a sample of urban paid workers in 10 West African countries.[2] The share of overeducated paid workers in these countries ranged from 5% in Burkina Faso to 25% in Congo DR, with almost 25% of paid workers being undereducated. More recent evidence for a sample of urban workers in low- and middle-income countries indicates large differences between worker education and the education level required for a job (Handel, Valerio, & Sánchez Puerta, 2016).[3] A mean matched rate of approximately 51.9% was found for all 11 countries. Countries such as Kenya, Bolivia, Lao DPR, Vietnam, Sri Lanka, and Ghana experienced the highest share of mismatch, ranging from 56.5% in Sri Lanka to 74% in Vietnam, with Ghana having a mismatch rate of 52.3%.

Different theoretical considerations have been put forward to explain the incidence and related costs of overeducation and undereducation in the labor market. Most notable among them are the human capital model (Becker, 1964) and the job competition model (Thurow, 1975). According to the human capital model, individual earnings should not be directly affected by job requirements, but instead earnings should be determined by the attained level of education. Overeducated and undereducated individuals should therefore be rewarded or penalized accordingly. In contrast, in the job competition model, the earnings of individuals are solely based on the requirements of the job, implying that overeducation and undereducation are not rewarded in the labor market.

This study aims to build on previous research to investigate the prevalence and effect of educational mismatch in Ghana, by gender and over time. The analysis uses cross-sectional data from three rounds of the Ghana Living Standards Survey (GLSS), 1998–1999, 2005–2006, and 2012–2013, to provide empirical evidence on the incidence and effects of educational mismatch on earnings for men and women. The realized matches method that uses modal values of completed years of education for each major occupational group is used to derive the measures of overeducation and undereducation. We also employ an alternative measure to construct a matching index for individuals in the sample based on their educational attainment, employment type, and occupation. Because the sample used for the earnings analysis consists of only working individuals, Heckman correction procedure (Heckman, 1979) is employed to address concerns relating to sample selection bias. The results from selectivity-corrected OLS earnings regressions were broadly in line with the literature and indicated positive returns for surplus education although the returns were smaller than those received by workers with the required years of education. The premium received was found to be greater for women. Women also received a penalty that was twice the penalty received by men for having fewer years of schooling than required. An analysis of the time dimension of educational mismatch and earnings showed that although the penalty associated with deficit schooling decreased over time for men, it increased marginally for women. In addition, women rather than men were associated with a significant increase in returns to having the required education level.

The remainder of this paper is organized as follows. Section 2 provides a brief background of education and the labor market in Ghana, followed by a description of the data and variables used for the analyses (Section 3). Next, the estimation techniques are described in Section 4 followed by a discussion of the results (Section 5). Section 6 concludes.

2 | EDUCATION AND THE LABOR MARKET IN GHANA

Ghana's economic growth has been remarkably strong, with its lowest economic growth of 3.3% recorded in 1994 and highest of 15% recorded in 2011 (Aryeetey & Baah-Boateng, 2015). Despite these improvements in the economic performance of Ghana, a major developmental concern is the ability of the country to translate this strong growth performance into job creation. With an annual average job creation growth of 3.2% between 1991 and 2005, the country has not been able to keep up with the increase in the potential workforce, which averages approximately 3.8% per year. Job creation increased to 4% between 2005 and 2012, but annual growth among the working population decreased to 2.6%, with economic growth averaging 8% per year over this period (See Honorati & de Silva, 2016 for a further discussion on job creation in Ghana). The low level and quality of human capital make it difficult for the benefits of growth to be spread through the creation of high-skilled and high-earning jobs (Aryeetey & Baah-Boateng, 2015). The majority of jobs are low skilled and require a limited use of cognitive skills (Handel et al., 2016; Honorati & de Silva, 2016). The prevalence of low-skilled jobs is partly explained by the low education level among the employed although it is also possible that the prevalence of low-skilled jobs could lead to lower levels of educational attainment. Nonetheless, Honorati and de Silva (2016) report that two out of five workers have no more than a primary education (first 6 years of formal education), and only one in five has more than a basic education, that is, primary and junior secondary school education.

The education system in Ghana has undergone a number of reforms over the past few decades. Figure 1 illustrates the structure of the education system in the late 1960s and the reform of 1987. Prior to the 1987 reform, pretertiary education consisted of 6 years of primary education; 4 and 5 years of middle and secondary school, respectively; and 2 years of A-level school. The 1970s saw further reforms, such as the introduction of junior secondary school and senior secondary school initiated by the Dzobo Committee. In 1987, the education system was reformed with the introduction of 12 years of pretertiary education consisting of 6 years of primary education, 3 years of junior secondary education, and 3 years of senior secondary education. The main objective of the 1987 reform was to expand and improve the quality of education in Ghana and make basic education free and equitable. The reform helped reverse the decline in enrolments that characterized the early 1980s (World Bank, 2004). The reform also aimed to contain, and partially recover, costs and to enhance sector management and budgeting procedures.

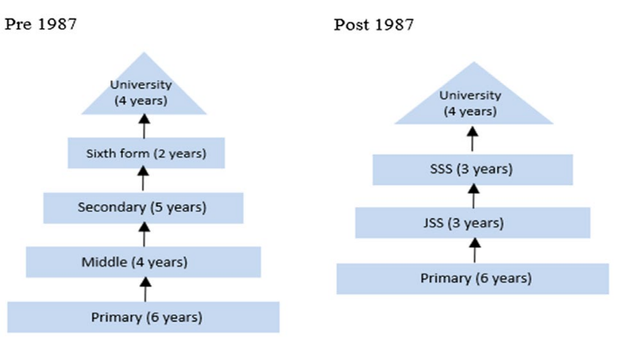

FIGURE 1 Education system in Ghana

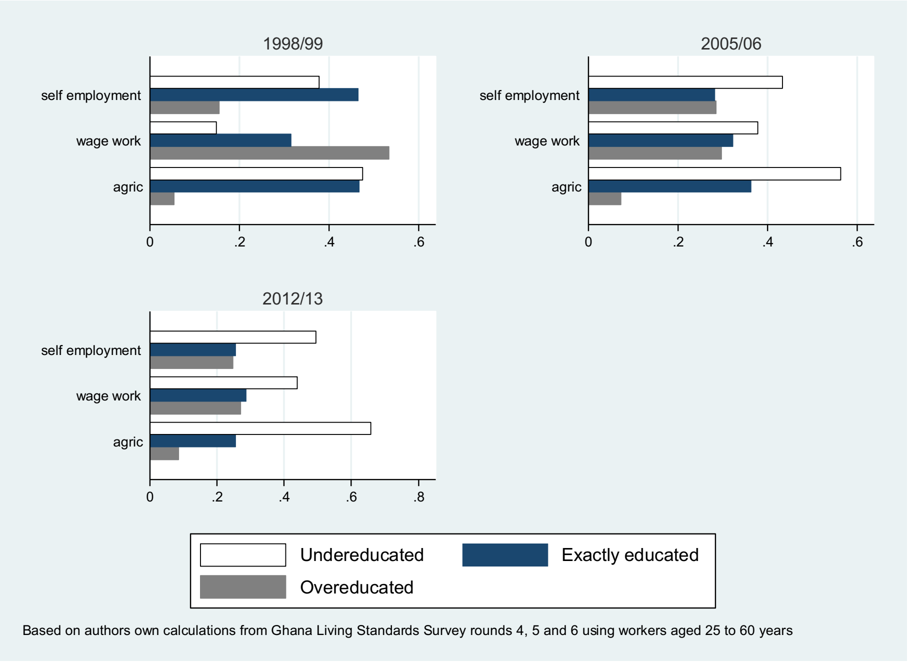

FIGURE 2 Incidence of educational mismatch by employment type, 1998–1999 to 2012–2013

A further review of the education system took place in 2007 under the New Patriotic Party, which led to the extension of the duration of senior high school from 3 to 4 years. However, this policy was short-lived, and in 2009, the government reverted to 3 years of senior high school (see Adu-Gyamfi, Donkoh, & Addo, 2016; Akyeampong, 2010; Akyeampong, Djangmah, Oduro, Seidu, & Hunt, 2007; Blunch & Hammer, 2018 for more discussion on the education system in Ghana).

There is evidence of educational mismatch in the Ghanaian labor market, with almost 50% of workers underqualified in 2005 (Honorati & de Silva, 2016). Figure 2 shows the incidence of educational mismatch by employment type from 1998–1999 to 2012–2013. The incidence of undereducation increased over this period and was particularly high among agricultural workers. Among wage workers, whose earnings are usually higher, the incidence of overeducation fell from 53.5% in 1998–1999 to 24.8% in 2012–2013, whereas undereducation increased from 37.9% to 44.1% in 2012–2013. The analysis detailed in this paper builds on this evidence.

3 | DATA AND VARIABLES

3.1 | Data

The data used are from the GLSS rounds 4–6. The GLSS is a nationally representative survey initiated in 1980 by the Policy Research Division of the World Bank. Round 4 of the survey was conducted in 1998–1999 and covered 300 enumeration areas. Rounds 5 (2005–2006) and 6 (2012–2013) covered 580 and 1,200 enumeration areas, respectively. The enumeration areas are stratified into 10 administrative regions, and each region is subdivided into rural and urban areas. Figure A1 shows the distribution of the sample across the 10 administrative regions. The total number of households surveyed was 6,000 in round 4; 8,687 in round 5; and 16,772 in round 6.

The survey collects detailed information on individual and household characteristics, as well as information on current education and employment status. The sample consists of individuals aged 25–60 years who have ever attended school and reported sufficient information to calculate their level of education (years of schooling completed) and other measures relevant for the study. In the analysis of earnings, the sample is restricted to those in work at the time of the survey, including the self-employed. The upper limit of 60 years reflects the official retirement age in Ghana. This restriction resulted in around 38,680 observations. We also excluded family workers and apprentice and domestic workers from the analysis[4] because earnings for this group of workers are difficult to measure. For instance, apprentices in Ghana are not paid directly but instead pay their "masters" to be trained. Similarly, domestic workers often receive other forms of nonwage compensation. This resulted in a further reduction in the sample to around 32,399 observations. In addition, the final sample is restricted to individuals for whom records of highest grade completed were available because they had attended school at some point even if this was for less than a year (zero completed schooling). Although in some occupations those who never attended school (zero education) could be disproportionately represented, including this group raises a number of issues. First, assigning educational attainment a value of 0 (to indicate that they have not completed any grade) for those who never attended school would treat this group of workers as if they were the same as those who attended school but not completed a grade. However, these two groups are not the same. In the case of the latter, some form of learning may have still taken place even though no grade was completed. The two groups could also be different in terms of other observables. Adding the group that never attended school would also skew the distribution. We therefore exclude these individuals from our analysis. This additional restriction led to a further reduction in the sample to around 22,436 who were in work.

In the regression analysis for earnings estimated for only individuals who were in work, the sample was reduced further due mainly to missing values for earnings as well as some other included independent variables, resulting in a final sample of 18,396 in the earnings regressions. Table A1 provides the summary statistics for the main variables used in the analysis. Table A2 provides descriptions for the main variables.

Men were marginally more represented in the full sample than women but were strongly represented in the employed sample. The majority of workers were in agriculture and services and sales occupations. These two occupation groups accounted for approximately 50% of the total share of employment. Women were disproportionately located in services and sales. Figure 3 shows the distribution of earnings for men and women between 1998–1999 and 2012–2013. The distribution for men lies to the right of the distribution for women, consistent with a gender wage gap. The Kolmogorov–Smirnov test of significance (Wilcox, 2005) suggests that this difference is highly significant.

3.2 | Educational mismatch measures

Three main methods (as noted in Section 1) have been used to derive measures of educational mismatch. The subjective method (self-assessment) is based on worker assessment of the level of educational attainment that is required to perform a job. This assessment is then compared with the worker's actual level of educational attainment to determine if they are matched or mismatched. Several drawbacks have been associated with this method. For instance, workers may not have the required level of information about the job, and therefore, their responses could be inaccurate (Leuven & Oosterbeek, 2011). Workers may also overstate the requirements of their job (Borghans & de Grip, 2000; Hartog, 2000), which could lead to a bias in their estimates (McGuinness, 2006; McGuinness, Pouliakas, & Redmond, 2018). Studies such as Dolton and Vignoles (2000), Belfield (2010), Daly et al. (2000),

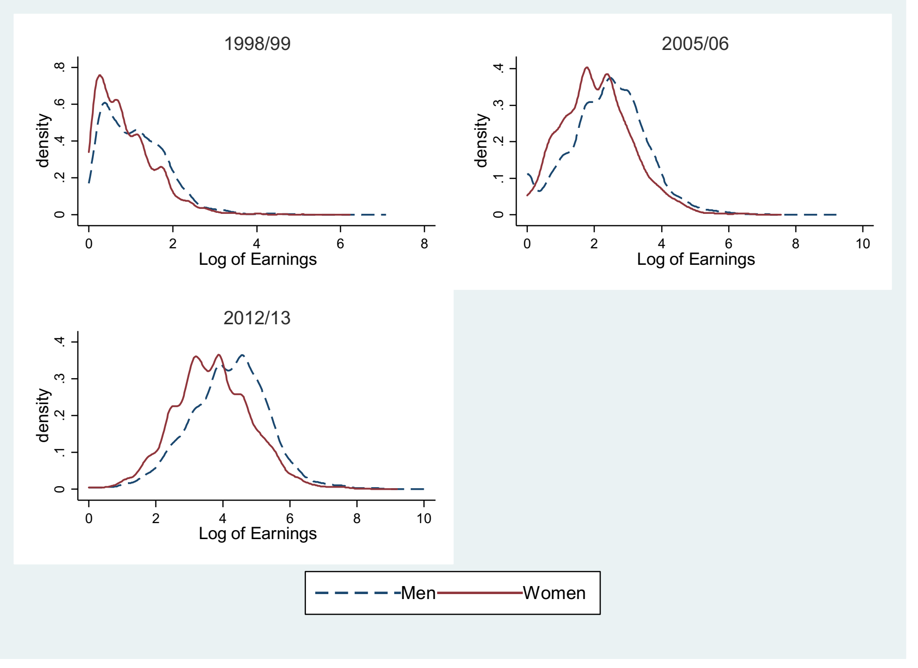

FIGURE 3 Gender differences in earnings, 1998–1999 to 2012–2013

and Battu, Belfield, and Sloane (2000) have used the subjective (self-assessment) method to measure educational mismatch.

The second method is the objective approach (job evaluation), which is based on evaluations by professional job analysts. The information generated from such analyses is documented in the *Dictionary of Occupational Titles* and subsequently the Occupational Information Network (BLS, 1999). While the objective approach is based on experts' assessments, a major drawback is that updates are carried out infrequently, largely because of the associated costs of collecting these data (Hartog, 2000; McGuinness et al., 2018; Verhaest & Omey, 2012). Furthermore, because the classifications are based on opinions, albeit of experts, this approach can still suffer from subjectivity bias. This method has been used by a number of authors including Sloane, Battu, and Seaman (1999), Green and Zhu (2010), Cohn and Ng (2000), and Verhaest and Omey (2009).

The final method is the realized matches (statistical) method, which relies on education and occupation information, both of which are readily available in many nationally representative surveys (Flisi, Goglio, Meroni, Rodrigues, & Vera-Toscano, 2017; Hung, 2008). An educational mismatch is determined if the worker's education level is above the mean or modal value for the occupational group (Kiker et al., 1997; Verdugo & Verdugo, 1989). A worker is overeducated if he or she has more years of education than is required. Conversely, a worker is undereducated if he or she has insufficient education to be hired for the job. An advantage of the realized matches approach is that the educational standard of the status-specific occupational benchmark is updated regularly to capture changing educational requirements over time. This method has been extensively used in the literature (Bauer, 2002; Chiswick & Miller, 2009, 2010; De Oliveira, Santos, & Kiker, 2000; Hartog, 2000; Herrera & Merceron, 2013; Mateos-Romero & Salinas-Jiménez, 2017; Ng, 2001; Quinn & Rubb, 2006; Rubb, 2014; Robst, 1994; Salinas-Jiménez, Rahona-López, & Murillo-Huertas, 2013; Verhaest & Omey, 2006; Yeo & Maani, 2017). Given the availability of information on education and occupation in the

GLSS data, the realized matches method is appropriate for this analysis. Using this method, the mismatch variables for the pooled sample are constructed by taking the modal value of years of completed schooling for individuals who ever attended school across the different occupations. However, we acknowledge that the realized matches method is imperfect. For example, as pointed out to us by an anonymous reviewer, the modal worker may be overeducated or undereducated in some occupations. For this reason, we also conduct the analysis using an alternative measure of educational mismatch (described later).

Measures of educational mismatch are usually decomposed to capture overeducation, required education, and undereducation (Duncan & Hoffman, 1981). This decomposition, often known as ORU, is useful for a number of reasons. ORU is able to combine information on attained education and required education while maintaining the continuous nature of both dimensions (Korpi & Tåhlin, 2009). In addition, the pattern of results for research that has used this approach has proven to be consistent (Rubb, 2003). We use the modal value of completed years of education for each major occupational group to derive measures of required education, overeducation, and undereducation. Compared with the mean approach, the modal approach reduces sensitivity to outliers and provides a more accurate measure of adequate education. In addition, the required years of education derived from this measure refer to the actual education levels of workers in a job, rather than fractions of years of education. Figure 4 shows the distribution of educational mismatch utilizing these measures. The proportion of overeducated workers remained fairly unchanged over the period. However, there was a continuous increase in the proportion of undereducated workers. For instance, between 1998–1999 and 2012–2013, the percentage of workers who were undereducated increased from 38% to 55%. Interestingly, the share of workers with the exact level of educational attainment for their occupations fell throughout the period from 43% in 1998–1999 to 25% in 2012–2013. These trends raise concerns about the education system and the labor market given recent advances in educational enrolment and participation.

Figure 5 shows the incidence of educational mismatch by gender over the three survey rounds. As shown, for both men and women, the proportion of workers in jobs that match their educational attainment consistently fell. In 1998–1999, 45.2% and 41.9% of men and women, respectively, had the required education for their jobs. These figures fell to 28.7% and 23.9% in 2012–2013. Undereducation increased throughout the period for both men and women although the incidence of undereducation

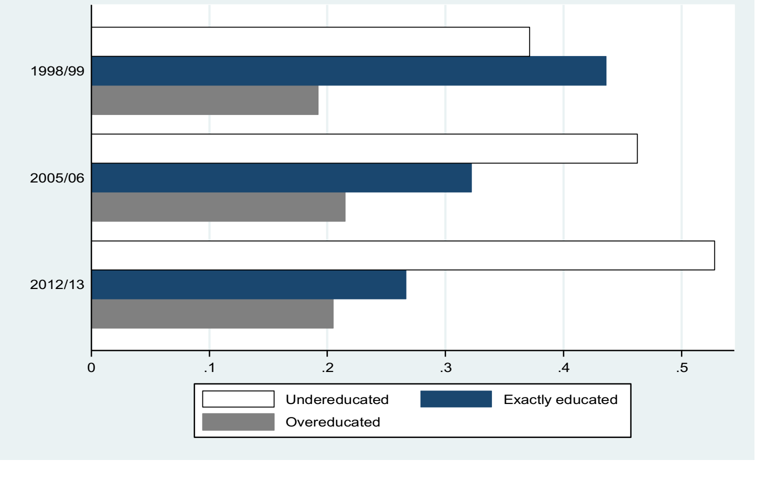

FIGURE 4 Incidence of educational mismatch over time

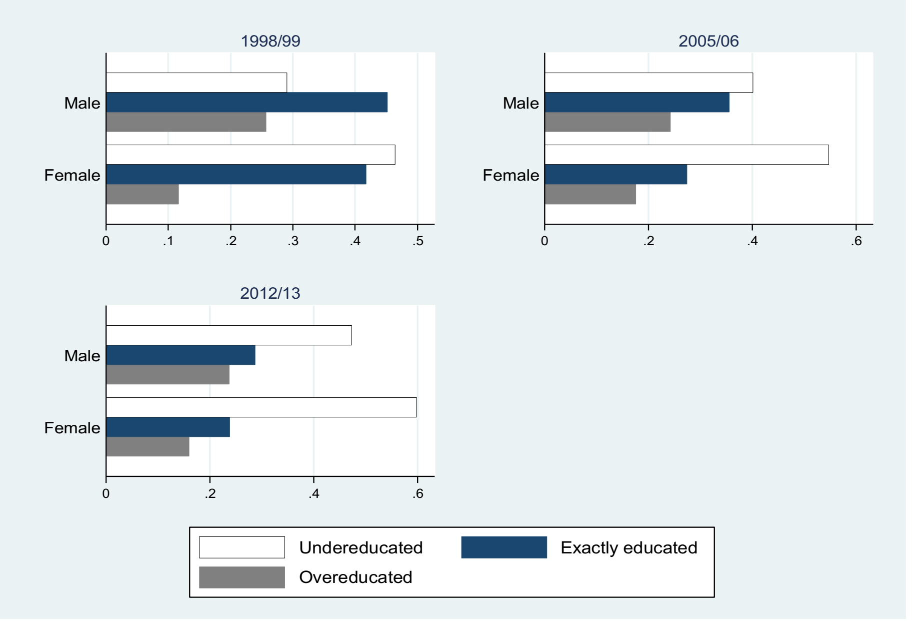

FIGURE 5 Incidence of educational mismatch by gender from 1998–1999 to 2012–2013

was higher among women; the incidence of female undereducation increased from 46% in 1998–1999 to 60% in 2012–2013. The increase in undereducation, especially among women, suggests that mismatches in the Ghana labor market remain a challenge to effective labor market performance. In terms of overeducation, men are more likely to have more than the required level of education needed for their jobs than women.

Figure 6 shows mismatches in years of schooling by gender for the three rounds of the survey. There are clear differences in educational attainment between men and women. The difference in average years of required education increased from approximately 10 and 10.2 in 1998–1999 (round 4) to approximately 10.3 and 10.8 in 2012–2013 for men and women, respectively. As the mismatch variables are constructed by pooling the sample and taking the modal values for each occupation, the increases in the years of required education are driven largely by changes in the occupational composition of individuals. With regard to years of overeducation, men accessed more schooling than women. For women, the extra years of schooling above the required level remained almost unchanged throughout the period. In contrast, women tended to have more years of deficit schooling than men although this fell from 3 years in 1998–1999 to 2.5 years in 2012–2013. The opposite was true for men: years of deficit schooling increased from almost 1.5 in 2005–2006 to 1.8 years in 2012–2013.

3.3 | Alternative education measure

Realizing some of the limitations inherent in measuring educational mismatch using, for instance, self-reported measures, and the possibility for the representative worker to be overeducated or undereducated in some occupations, we adopt an approach as an additional measure of (mis)match that reflects the outcome of supply and demand in the labor market (Boualam, 2014). The pooled sample is

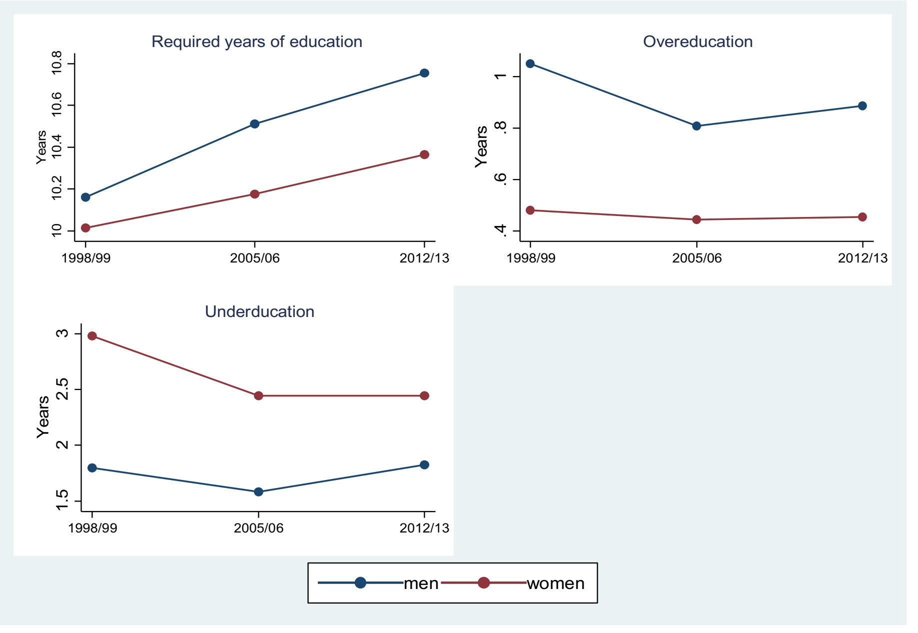

FIGURE 6 Educational mismatch (years) by gender for working individuals

used to construct a matching index for each individual at the educational attainment level, for employment type and occupation. This index is defined as.

$$\text{match}_{\text{educ,emp,occ}} = \frac{\text{share}_{\text{educ,emp,occ}}}{\text{share}_{\text{occ}}^{\max}}, \tag{1}$$

where

$$\text{share}_{\text{educ,emp,occ}} = \frac{N_{\text{educ,emp,occ}}}{N_{\text{occ}}}$$

and

$$\text{share}_{\text{occ}}^{\max} = \max_{\text{educ}} \left\{ \text{share}_{\text{educ,emp,occ}} \right\}.$$

$N_{\text{educ,emp,occ}}$ represents the total number of workers with a given educational attainment, educ, in a given employment type, emp, within an occupation, occ. N_{occ} is the total number of workers in a given occupation. $\text{share}_{\text{educ,emp,occ}}$ represents the share of workers in a given occupation and employment type with a given educational attainment. $\text{share}_{\text{educ,emp,occ}}$ is rescaled by dividing by the maximum value, $\text{share}_{\text{occ}}^{\max}$, that can be observed for all educational attainment levels within each occupation. A coefficient close or equal to 0 indicates that this type of educational attainment is rarely observed within the occupation, and a coefficient close or equal to 1 indicates a match.

An advantage of this approach is that it does not assume that only one level of educational attainment is ideal for a given occupation. Different matches may be observed in any given occupation. In addition, the measure is continuous, thus allowing us to observe a full range of values reflecting

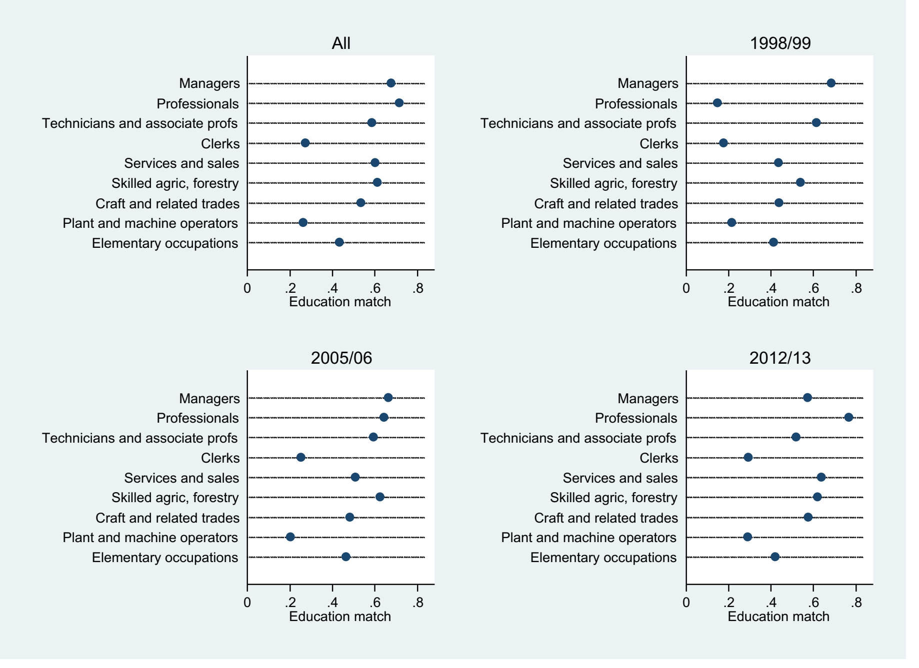

FIGURE 7 Educational match by occupation

variation in education and occupation. Figure 7 shows the average match index for each occupation in each year from 1998–1999 to 2012–2013. The coefficient of match for professionals increased from approximately 0.2 in 1998–1999 to almost 0.8 in 2012–2013. The level of match among managerial occupations remained similar over the same periods, as was also the case for plant and machine operator occupations. Clerical occupations had the lowest level of match over the three periods.

4 | ECONOMETRIC METHODOLOGY

4.1 | Estimation technique

We examine the returns to education using augmented Mincer-earning-type regressions. As the sample used in these estimations consisted of only employed individuals for whom earnings were observed, any estimates that failed to consider selection into employment would yield biased estimates, partly because the sample of employed individuals may not be a random subset of the population. The willingness of individuals to supply labor may therefore not be randomly assigned. We address this issue using the Heckman selection procedure (Heckman, 1979) by first deriving the inverse Mills ratio (IMR), also referred to as Heckman's lambda, from the employment participation equation estimated using probit. The selection term (IMR) is then included as an additional explanatory variable in the earnings equation. The estimated employment participation equation is of the form.

$$\mathrm{PR}(\mathrm{Employed}_i = 1) = x_i\beta + g_i\theta + j_i\gamma + \varepsilon_i, \tag{2}$$

where Employed indicates the employment status of the individual, with 1 indicating that the individual is currently employed and 0 if not employed. x_i is a vector of individual characteristics, including gender, age, and marital status. j_i is a vector of the round, location, and region dummies. g_i consists of variables that are not included in the earnings regressions but satisfy the exclusion restrictions. The restriction requires that these variables should directly affect employment probability but should not have a direct effect on earnings. We use the number of young children (less than 6 years) in the household and the local average share of working individuals. Our rationale for including these variables is that young children may impose a time constraint and can therefore affect the individual's participation in work (Huber & Mellace, 2014; Mulligan & Rubinstein, 2008), particularly for women. Older children, on the contrary, are less dependent and less likely to affect the respondent's employment decision. Similarly, the local share of workers is a possible indicator of community economic development so that individuals in communities with a larger share of workers will be more likely to find jobs.[5] Pagán (2002) finds that a number of working individuals have positive and significant effects on employment propensity. These variables can affect the decision to work but will not directly affect earnings. The employment participation equations are estimated jointly and separately for men and women.

The second stage of the estimation focuses on earnings. The earnings regression includes the Heckman selection term, IMR (or lambda). The equation estimated is of the form.

$$\ln y_i = z_i\beta + \varphi_r \mathrm{REQEDUC} + \varphi_0 \mathrm{OVEREDUC} + \varphi_\mathrm{u} \mathrm{UNDEREDUC} + \alpha \mathrm{IMR} + j_i\gamma + \varepsilon_i, \tag{3}$$

where $\ln y_i$ is the log of weekly earnings of individual i. REQEDUC, OVEREDUC, and UNDEREDUC are the required education, overeducation, and undereducation, respectively, all in years. IMR (lambda) is the Heckman selection term derived from Equation 2. z_i is a vector of individual characteristics, including gender and marital status. z_i also includes the number of hours worked per week, experience (calculated as age minus years of schooling minus compulsory school start age [6 years]), and its square and employment type. j_i is as previously defined and is a vector of round, location, and region dummies. The data collection round and location dummies capture any possible effect of time on earnings. j_i also includes occupational dummies.

Finally, we estimate the returns to education using the alternative index measure ($\mathrm{match}_{\mathrm{educ,emp,occ}}$) of educational match as specified in Equation 1 as an independent variable. The estimated equation is of the form.

$$\ln y_i = z_i\beta + \varphi_r \mathrm{Match} + \alpha \mathrm{IMR} + j_i\gamma + \varepsilon_i. \tag{4}$$

All parameters are as previously defined.

4.2 | Potential estimation issues

Equation 3 assumes that the education variables are exogenous. However, the literature on returns to education shows that education is endogenous due to certain unobserved factors that influence the individual's ability to acquire more years of schooling (while not having an independent effect on an individual's earnings) as well as measurement errors (Bauer, 2002; Harmon, Oosterbeek, & Walker, 2003; Korpi & Tåhlin, 2009). As such, all three measures of education may be endogenous and therefore must be accounted for using instrumental variables (Leuven & Oosterbeek, 2011). To apply the instrumental variables technique to produce acceptable estimates, they must satisfy two conditions: relevance and exogeneity. Regarding relevance, there should be a correlation between the instrument and endogenous regressor. Exogeneity requires no correlation between the instrument and error term.

Previous studies address this issue using retrospective data on the place of residence during childhood, economic problems, and disruptions in the family of origin, number of siblings, and family background (Dearden, 1999a; Dolton & Silles, 2008; Harmon et al., 2003; Korpi & Tåhlin, 2009). Other studies use panel data to estimate fixed effects regressions to control for unobserved, time-invariant factors (Bauer, 2002; Dolton & Silles, 2008).

A key challenge faced with the GLSS data is that there are no retrospective questions on childhood circumstances, such as the number of schools available in a neighborhood, family background, ability, and economic conditions, that can be used as potential instruments for education in the main estimation equation (Equation 2).[6] Dearden (1999b), however, examines the accuracy of OLS coefficients against results that attempt to eliminate biases from OLS estimates, such as measurement error and endogenous education choices. The conclusion from Dearden (1999b) is that failure to control for ability and family background characteristics that influence education choices will bias OLS estimates upward, whereas measurement error can only lead to a downward bias. Given our inability to fully address possible endogenous education choices, we proceed cautiously with the OLS estimations that we believe are fairly reasonable estimates of the true returns to education and generate effects that are, in most cases, of the same direction as one would have achieved with IV estimates. We are mindful of this caveat and therefore refrain from making any causal claims from our findings and instead interpret all coefficients as associations.

5 | RESULTS

5.1 | Employment participation and returns to education for working individuals

This section presents the results from employment participation regressions and OLS selectivity-corrected earnings regressions. The results from the first-stage participation regressions are presented in columns (1)–(3) of Table 1. An immediate observation is that the coefficients for the number of younger children are negative and significant in the pooled regression and also for women. The share of working individuals at the local level is also positive and significant. The results clearly suggest that especially for women, having more young children decreases the probability of being employed, as evidenced in the literature. For men, this is not the case. In addition, living in a location with a larger share of individuals working significantly improves employment probability. The coefficient on the gender dummy is negative and significant, suggesting that women are less likely to be employed than men.

The estimates for the OLS selectivity-corrected earnings regressions in columns (4)–(6) of Table 1 provide pooled and separate earnings regressions for men and women. Including indicators of required, overeducation, and undereducation separately allows for different effects on earnings. The dependent variable in both models is the natural logarithm of weekly earnings. Across all specifications, the selectivity term, IMR (lambda) is positive and mostly significant. This indicates that individuals with the average characteristics of those who select into employment earn higher earnings than would individuals drawn randomly from the population with comparable characteristics.

For brevity, we focus on the education mismatch measures. In the pooled regression (column 4), the coefficients of required education, overeducation, and undereducation have the expected signs and are statistically significant at all levels. Each year of schooling beyond that required increases earnings by 8.7%. Despite the positive returns to overeducation, this effect is less than the earnings associated

TABLE 1 Employment participation and effects of education on earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Employment participation			**Earnings**					
	Pooled	**Men**	**Women**	**Pooled**	**Men**	**Women**	**Pooled**	**Men**	**Women**
Number of young children	–0.0414***	0.007	–0.0757***						
	(0.0121)	(0.0189)	(0.0163)						
Local average share of workers	2.4542***	2.776***	2.173***						
	(0.0739)	(0.1075)	(0.1037)						
Required education				0.2922***	0.3560***	0.1473*			
				(0.0404)	(0.0486)	(0.0760)			
Overeducation				0.0871***	0.0771***	0.1028***			
				(0.0038)	(0.0045)	(0.0072)			
Undereducation				–0.0376***	–0.0294***	–0.0456***			
				(0.0026)	(0.004)	(0.004)			
Education match							0.217***	0.256***	0.196***
							(0.0355)	(0.0461)	(0.0566)
Female	–0.381***			–0.3639***			–0.414***		
	(0.0207)			(0.0175)			(0.0179)		
Marital status: Other	–0.1296***	–0.196***	–0.114***	–0.1186***	–0.1936***	–0.0566**	–0.153***	–0.254***	–0.0573***
	(0.0240)	(0.0407)	(0.0303)	(0.0153)	(0.0220)	(0.0221)	(0.0155)	(0.0219)	(0.0225)
Marital status: Never married	–0.648***	–0.943***	–0.39***	–0.2472***	–0.3461***	–0.1269***	–0.307***	–0.476***	–0.144***
	(0.0334)	(0.0480)	(0.0497)	(0.0304)	(0.0427)	(0.0471)	(0.0310)	(0.0430)	(0.0493)
Age (years)	0.0088***	–0.002**	0.0016***						
	(0.001)	(0.002)	(0.002)						
Experience				0.0154***	0.0148***	0.0160***	–0.0031	–0.003	–0.005
				(0.003)	(0.0043)	(0.0043)	(0.003)	(0.0042)	(0.0042)

(Continues)

TABLE 1 (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Employment participation			Earnings					
	Pooled	Men	Women	Pooled	Men	Women	Pooled	Men	Women
Experience squared				–0.0002***	–0.0002***	–0.0001*	0.0000	–0.0000	0.0001
				(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Hours of work				0.0038***	0.003***	0.0043***	0.0035***	0.0024***	0.0043***
				(0.0004)	(0.001)	(0.001)	(0.0004)	(0.001)	(0.0001)
Round 5	0.7513***	1.034***	0.5299***	1.3073***	1.412***	1.1256***	1.394***	1.475***	1.243***
	(0.0375)	(0.0560)	(0.0513)	(0.0210)	(0.0285)	(0.0371)	(0.0223)	(0.030)	(0.0401)
Round 6	0.673***	0.967***	0.524***	2.853***	2.998***	2.604***	2.925***	3.035***	2.721***
	(0.0343)	(0.0517)	(0.0467)	(0.0209)	(0.0273)	(0.0387)	(0.0221)	(0.0290)	(0.0410)
Wage employment				–0.130***	–0.193***	–0.0977***	–0.0247	–0.139***	0.0818**
				(0.0201)	(0.0267)	(0.0337)	(0.0201)	(0.0268)	(0.0340)
Agriculture				–0.719***	–0.798***	–0.606***	–0.786***	–0.898***	–0.658***
				(0.0303)	(0.0456)	(0.0466)	(0.0315)	(0.0463)	(0.0488)
IMR (lambda)				0.184***	0.154*	0.166*	0.0812*	0.216*	0.0231
				(0.0625)	(0.0864)	(0.0927)	(0.0575)	(0.0888)	(0.0747)
Rho				0.189	0.165	0.180	0.087	0.223	0.024
Sigma				0.969	0.933	0.923	0.933	0.925	0.927
Location FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE				Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.15	0.19	0.10	0.68	0.69	0.66	0.66	0.68	0.64
Observations	26,456	14,375	12,081	18,396	10,306	8,090	18,396	10,306	8,090

Note: IMR = inverse Mills ratio; robust standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; pseudo R-squared reported for columns (1)–(3).

with individuals that have the required years of schooling (0.29). Regarding undereducation, there is a penalty of 3.7% for each year of deficit schooling. The direction of the effect is the same for both men and women (columns 5 and 6) although the penalty received for deficit schooling is larger for women than for men. Women with fewer years of schooling experience an earnings loss that is almost twice (4.6) the loss suffered by their male counterparts (2.9). The direction of the effects of the education mismatch variables is in line with the literature (Hartog, 2000; Kiker et al., 1997). The gender differences in returns to undereducation are also consistent with some previous research (Salinas-Jiménez et al., 2013) but contrary to others.

Columns (7)–(9) show the results of the estimations that use the alternative index measure of educational (mis)match. The OLS results indicate that an increase in educational match increases earnings by 0.22. The coefficients are larger for men than for women, in line with the coefficients for required education in columns (5) and (6), with earnings increasing by 0.26 for men compared with 0.2 for women. As in column (4), the coefficient on the gender dummy is negative, confirming that women earn lower wages. The signs of the other variables are similarly uncontentious.

5.2 | Educational mismatch and differences in returns over time

This section provides a brief analysis of differences in the effects of mismatch over time. This is done by including interaction terms between the survey round indicators and the three measures of education. Table 2 presents the results of these estimations. We comment only on the interaction terms.

In columns (1)–(3), the interactions between the survey rounds 5 and 6 and required education indicate an increase in earnings relative to round 4 although only marginally for the pooled sample. Only women experienced a significant increase in returns to required education in rounds 5 and 6 compared to round 4. Interestingly, there were no significant returns to overeducation for both men and women over the three periods although the effects were positive. Overall, there was a negative effect of undereducation on earnings, shown by the interaction between the survey rounds and undereducation. The negative effect of undereducation was larger for men than for women over the period. However, while the penalty associated with undereducation decreased for men between survey rounds 5 and 6, the penalty suffered by women for being undereducated increased. Columns (4)–(6), which used the index measure of match, show that earnings for both men and women increased over time with increased educational match.

As a sensitivity check, we generated another measure of match by comparing the individual's level of educational attainment with the level of education required by occupational group (ILO, 2014) using the definitions in the International Standard for the Classification of Occupations (ILO, 2012) and the associated skill level according to the International Standard Classification of Education (UNESCO Institute for Statistics, 2012). To derive the measure, the major occupation groups were grouped into four, and a level of educational attainment was assigned to each.[7] A match occurs if workers in a particular group have the assigned level of educational attainment. Those with a lower (higher) level of education for the occupation are considered undereducated (overeducated). This approach to determining a mismatch has been used elsewhere in the literature (Kalfa & Piracha, 2017; Mateos-Romero & Salinas-Jiménez, 2017). The results from these estimations are presented in Table A3. The results are consistent with the results in Table 1; overeducated individuals receive a wage premium compared with those with the assigned level of education, whereas undereducated individuals pay a penalty relative to those who have the required education level for their occupational group.

TABLE 2 Differences over time in the effects of education on earnings

DV: Log of weekly earnings	(1) Pooled	(2) Men	(3) Women	(4) Pooled	(5) Men	(6) Women
Required education	0.2358***	0.3425***	0.0335			
	(0.0456)	(0.0534)	(0.0902)			
Overeducation	0.0818***	0.0789***	0.0969***			
	(0.006)	(0.007)	(0.010)			
Undereducation	−0.0176***	−0.0094**	−0.0321***			
	(0.0030)	(0.005)	(0.004)			
Education match				−0.373***	−0.282***	−0.837***
				(0.0778)	(0.0949)	(0.153)
Round 5	1.063***	1.286***	0.376	1.124***	1.220***	0.785***
	(0.102)	(0.119)	(0.332)	(0.0484)	(0.0568)	(0.0962)
Round 6	2.606***	2.951***	1.784***	2.604***	2.756***	2.1515***
	(0.0991)	(0.113)	(0.333)	(0.0462)	(0.0541)	(0.0920)
Round 5 * required education	0.0277***	0.0169	0.0773**			
	(0.0096)	(0.0109)	(0.0325)			
Round 6 * required education	0.0288***	0.0092	0.0854***			
	(0.0093)	(0.0103)	(0.0326)			
Round 5 * overeducation	0.0181*	0.0106	0.0183			
	(0.0093)	(0.0115)	(0.0159)			
Round 6 * overeducation	0.0015	−0.0100	0.0029			
	(0.0081)	(0.0010)	(0.0143)			
Round 5 * undereducation	−0.030***	−0.0372***	−0.0173**			
	(0.0055)	(0.0083)	(0.0075)			

(Continues)

TABLE 2 (Continued)

DV: Log of weekly earnings	(1) Pooled	(2) Men	(3) Women	(4) Pooled	(5) Men	(6) Women
Round 6 * undereducation	−0.0282***	−0.0238***	−0.0205***			
	(0.0053)	(0.0080)	(0.0074)			
Round 5 * education match				0.604***	0.613***	0.954***
				(0.0989)	(0.1224)	(0.184)
Round 6 * education match				0.705***	0.651***	1.179***
				(0.0901)	(0.111)	(0.168)
Female	−0.366***			−0.418***		
	(0.0175)			(0.0176)		
Marital status: Other	−0.117***	−0.193***	−0.0551**	−0.152***	−0.251***	−0.0564***
	(0.0153)	(0.0220)	(0.0221)	(0.0155)	(0.0220)	(0.0224)
Marital status: Never married	−0.250***	−0.345***	−0.1309***	−0.314***	−0.469***	−0.345***
	(0.0303)	(0.0428)	(0.0471)	(0.0310)	(0.0430)	(0.0493)
Experience	0.0164***	0.0152***	0.0170***	−0.00021	−0.0016	−0.0039
	(0.0030)	(0.0043)	(0.0043)	(0.0030)	(0.0042)	(0.0043)
Experience squared	−0.0002***	−0.0003***	−0.0002*	0.0000	−0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Hours of work	0.0038***	0.0030***	0.0043***	0.0035***	0.0024***	0.0043***
	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0006)
Wage employment	−0.129***	−0.192***	−0.0977***	−0.0452**	−0.159***	0.0471
	(0.0201)	(0.0266)	(0.0337)	(0.0203)	(0.0271)	(0.0343)
Agriculture	−0.712***	−0.804***	−0.599***	−0.796***	−0.892***	−0.684***
	(0.0310)	(0.0457)	(0.0482)	(0.0316)	(0.0465)	(0.0491)

(Continues)

TABLE 2 (Continued)

DV: Log of weekly earnings	(1) Pooled	(2) Men	(3) Women	(4) Pooled	(5) Men	(6) Women
IMR (lambda)	0.182***	0.150*	0.163*	0.090*	0.214**	0.025
	(0.0560)	(0.0786)	(0.0796)	(0.0641)	(0.0884)	(0.0721)
Rho	0.189	0.162	0.175	0.093	0.231	0.028
Sigma	0.963	0.931	0.932	0.974	0.924	0.892
Location FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.68	0.69	0.66	0.66	0.68	0.64
Observations	18,396	10,306	8,090	18,396	10,306	8,090

Note: IMR = inverse Mills ratio; robust standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

6 | CONCLUSIONS

We have examined gender differences in educational mismatch for employed workers in the Ghanaian labor market and the implications of mismatch on earnings. The empirical analysis was based on cross-sectional data from three rounds of the GLSS, 1998–2013. The realized matches approach to measuring educational mismatch was used in addition to an alternative method that does not assume that only one level of educational attainment is ideal for a given occupation.

The results from the selectivity-corrected OLS earnings regressions are broadly in line with the literature. First, there are positive returns to surplus education although the returns are smaller than the returns received by workers with the required years of education. The premium for overeducation was found to be greater for women. Second and in contrast to the results for surplus and required education, workers with fewer years of schooling than that required for their jobs received a penalty. Women received a penalty that was twice the penalty received by men for having fewer years of schooling than required. The results from the alternative measure also showed that individuals with a better match were associated with higher earnings although the effects were larger for men than for women. Last, we considered differences in the effects of educational mismatch over time. We found that while the penalty associated with deficit schooling decreased over time for men, it increased for women. In addition, women rather than men were associated with a significant increase in returns to required education. The lack of significance of returns to overeducation over time indicates that there are disconnects in the linkages between Ghana's educational system and the labor market; the value of human capital beyond the required level may erode over time, representing a waste of public resources.

The policy significance of these results does not lie only in the fact that they provide evidence of educational mismatch. The results also indicate that educational mismatch, in particular undereducation, is more prevalent among women. There are possible repercussions for the Ghanaian labor market. The fact that employers are hiring workers with fewer years of education than required for their job indicates a possible skill shortage. To improve the labor market position of Ghanaians, particularly women, better access to quality education is needed to ensure that people leave school with the required skills and knowledge. It is also important for individuals to consider their educational investment decisions carefully. Accurate knowledge of occupation-specific requirements would help individuals to choose the right amount of education. Although it is important to create jobs, there is a need to improve the effectiveness of the search and hiring methods of firms. Specifically, it is imperative to reduce reliance on personal and social networks in labor market recruitment, commonly referred to as "who-you-know" and shift to a system based on merit. This shift could help ensure that more individuals are employed in jobs that match their level of education.

The results presented in this study indicate associations rather than causations, mainly because of our inability to identify strong instruments that could have been used to identify possible causal mechanisms of the effects of education on earnings. Although other studies have also proceeded in this way, it is important for future studies in developing countries to address issues of endogeneity to enable a better understanding of how a mismatch in employment impacts earnings. In addition, the use of panel data to unravel some of the unobserved heterogeneities would provide a further understanding of the phenomenon. A further limitation of this study is that the sample used consists of only individuals who ever attended school. Future research could benefit from the consideration of those who never attended school. This group may have particular characteristics that are important for extending the understanding of earnings differentials. In addition, the use of years of completed schooling to construct measures of educational mismatch is unable to capture aspects of education quality, which has mostly been found to induce higher years of schooling (Castelló-Climent & Hidalgo-Cabrillana, 2012; Dearden, Ferri, & Meghir, 2002; Harmon & Walker, 2000). This limits our ability to make any inferences about how the mismatch variables could be affected by education quality. Further research is needed to understand the role of education quality in mismatches in the labor market. Last, future surveys of developing country labor markets should provide more detailed measures of education quality, skills, and information on job requirements that are comparable with labor market surveys in most developed countries. This would enable a more comprehensive analysis of how different kinds of educational and skill mismatches, as well as education quality, affect individual earnings across countries and between regions. Most importantly, these surveys need to be nationally representative, and coverage should be for all sectors.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are from the fourth (1998–1999), fifth (2005–2006), and sixth (2012–2013) rounds of the Ghana Living Standards Survey available from the Ghana Statistical Services at https://www.statsghana.gov.gh/gssdatadownloadspage.php.

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ENDNOTES

[1] This body of evidence is associated with three main methods to measuring mismatch. Belfield (2010), Daly et al. (2000), and Dolton and Vignoles (2000) use the subjective/self-assessment method, whereas Hartog (2000) and Kiker et al. (1997) use the realized matches method. Cohn and Ng (2000) employ the objective method. Rubb (2003) and Groot and Van den Brink (2000) use a meta-analysis that consists of the different methods. See McGuinness (2006) for an overview of the literature on overeducation.

[2] The sample of countries analyzed included Benin, Burkina Faso, Cameroun, Congo DR, Cote D'Ivoire, Madagascar, Mali, Niger, Senegal, and Togo.

[3] The countries analyzed were Armenia, Bolivia, Georgia, Ghana, Kenya, Macedonia, Lao DPR, Sri Lanka, Ukraine, Yunnan Province (China), and Vietnam.

[4] In a separate analysis that is not reported, we included this group of workers. The results from these estimations remained fairly unchanged.

[5] In separate results not reported here, we excluded the local share of working individuals as an exclusion restriction. The results from these estimations were similar.

[6] We made attempts to address endogeneity concerns by experimenting with a number of potential instruments for the education variable, that captured exogenous variations in developmental progress and education policy, as well as family background. The measures included women's property rights at birth (see, e.g., Allendorf, 2007; Mishra & Sam, 2016 on women's property rights and children's educational attainment); local average years of schooling at year of birth; and rainfall at age 15 years. The 1987 education policy reform was also used as an instrument as education policy reform has been used in previous research as instrument for education (Denny & Harmon, 2000; Meghir & Palme, 1999). Postestimation tests from these estimations showed that the instruments were weak (failing to satisfy the relevance criteria) and therefore could not be used in instrumental variables regression.

[7] Major group 9 is assigned primary or less educational attainment, major groups 4–8 are assigned junior secondary and middle school educational attainment, major group 3 is assigned secondary educational attainment, and major group 1 is assigned post-secondary and tertiary educational attainment.

REFERENCES

Adu-Gyamfi, S., Donkoh, W. J., & Addo, A. (2016). Educational reforms in Ghana: Past and present. *Journal of Education and Human Development*, *5*(3), 158–172.

Akyeampong, K. (2010). *Educational expansion and access in Ghana: A review of 50 years of challenge and progress*. Sussex, UK: Centre for International Education, University of Sussex.

Akyeampong, K., Djangmah, J., Oduro, A., Seidu, A., & Hunt, F. (2007). *Access to basic education in Ghana: The evidence and the issues* (Project report). Consortium for Research on Educational Access, Transitions and Equity (CREATE), Falmer, UK and Winneba, Ghana.

Allendorf, K. (2007). Do women's land rights promote empowerment and child health in Nepal? *World Development*, *35*(11), 1975–1988.

Aryeetey, E., & Baah-Boateng, W. (2015). *Understanding Ghana's growth success story and job creation challenges* (WIDER Working Paper No. 2015/140).

Battu, H., Belfield, C. R., & Sloane, P. J. (2000). How well can we measure graduate over-education and its effects? *National Institute Economic Review*, *171*(1), 82–93. https://doi.org/10.1177/002795010017100107

Bauer, T. K. (2002). Educational mismatch and wages: A panel analysis. *Economics of Education Review*, *21*, 221–229.

Becker, G. (1964). *Human capital: A theoretical and empirical analysis with special reference to education*. New York: Columbia University Press.

Belfield, C. (2010). Over-education: What influence does the workplace have? *Economics of Education Review*, *29*(2), 236–245.

Blunch, N.-H., & Hammer, J. S. (2018). *The last of the lost generations? Formal and non-formal education in Ghana during times of economic decline and recovery* (IZA Discussion Paper No. 11513). Available at SSRN: https://ssrn.com/abstract=3177390.

Borghans, L., & de Grip, A. (2000). The debate in economics about skill utilization. In L. Borghans, & A. de Grip (Eds.), *The overeducated worker? The economics of skill utilization* (pp. 3–23). Cheltenham, UK: Edward Elgar.

Boualam, B. (2014). *Getting a first job: Quality of the labor matching in French cities*. Mimeo: University of Geneva.

Bureau of Labour Statistics (BLS) (1999). *Revising the standard occupational classification system*. Washington, DC: US Department of Labor.

Castelló-Climent, A., & Hidalgo-Cabrillana, A. (2012). The role of educational quality and quantity in the process of economic development. *Economics of Education Review*, *31*(4), 391–409.

Chiswick, B. R., & Miller, P. W. (2009). The International transferability of immigrants human capital. *Economics of Education Review*, *28*(2), 162–169.

Chiswick, B., & Miller, P. W. (2010). Does the choice of reference levels of education matter in the ORU earnings equation? *Economics of Education Review*, *29*(6), 1076–1085.

Cohn, E., & Ng, Y. C. (2000). Incidence and wage effects of overschooling and underschooling in Hong Kong. *Economics of Education Review*, *19*(2), 159–168.

Daly, M. C., Büchel, F., & Duncan, G. J. (2000). Premiums and penalties for surplus and deficit education: Evidence from the United States and Germany. *Economics of Education Review*, *19*(2), 169–178.

Dearden, L. (1999a). The effects of families and ability on men's education and earnings in Britain. *Labour Economics*, *6*, 551–567.

Dearden, L. (1999b). *Qualifications and earnings in Britain: How reliable are conventional OLS estimates of the returns to education* (IFS Working Paper No 99/7).

Dearden, L., Ferri, J., & Meghir, C. (2002). The effect of school quality on educational attainment and wages. *Review of Economics and Statistics*, *84*(1), 1–20.

Denny, K., & Harmon, C. (2000). *Education policy reform and the return to schooling from instrumental variables* (Institute for Fiscal Studies Working Papers W00/06).

De Oliveira, M. M., Santos, M. C., & Kiker, B. F. (2000). The role of human capital and technological change in overeducation. *Economics of Education Review*, *19*(2), 199–206.

Dolton, P., & Silles, M. (2008). The effects of over-education on earnings in the graduate labour market. *Economics of Education Review*, *27*(2), 125–139.

Dolton, P., & Vignoles, A. (2000). The incidence and effects of overeducation in the UK graduate labour market. *Economics of Education Review*, *19*(2), 179–198.

Duncan, J., & Hoffman, S. (1981). The incidence and wage effects of overeducation. *Economics of Education Review*, *1*(1), 75–86.

Flisi, S., Goglio, V., Meroni, E., Rodrigues, M., & Vera-Toscano, E. (2017). Measuring occupational mismatch: Overeducation and overskill in Europe—Evidence from PIAAC. *Social Indicators Research*, *131*, 1211–1249.

Green, F., & Zhu, Y. (2010). Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. *Oxford Economic Papers*, *62*(4), 740–763. https://doi.org/10.1093/oep/gpq002

Groot, W., & van den Brink, H. (2000a). Overeducation in the labour market: A meta-analysis. *Economics of Education Review*, *19*(2), 149–158.

Groot, W., & van den Brink, H. (2000b). Skill mismatches in the Dutch labour market. *International Journal of Manpower*, *21*(8), 584–595.

Handel, M. J., Valerio, A., & Sánchez Puerta, M. L. (2016). *Accounting for mismatch in low- and middle-income countries: Measurement, magnitudes, and explanations*. Available from https://openknowledge.worldbank.org/bitstream/handle/10986/24906/9781464809088.pdf?sequence=4&isAllowed=y.

Harmon, C., Oosterbeek, H., & Walker, I. (2003). The returns to education: Microeconomics. *Journal of Economic Surveys*, *17*(2), 115–156.

Harmon, C., & Walker, I. (2000). The returns to the quantity and quality of education: Evidence for men in England and Wales. *Economica*, *67*(265), 19–35.

Hartog, J. (2000). Over-education and earnings: Where are we, where should we go? *Economics of Education Review*, *19*(2), 131–147.

Heckman, J. J. (1979). Sample bias as a specification error. *Econometrica*, *47*, 153–161.

Herrera, J., & Merceron, S. (2013). Underemployment and job mismatch in sub-Saharan Africa. In P. De Vreyer, & F. Roubaud (Eds.), *Urban labor markets in sub-Saharan Africa*. Africa Development Forum series. Washington, DC: World Bank. https://doi.org/10.1596/978-0-8213-9781-7

Honorati, M., & de Silva, S. J. (2016). *Expanding job opportunities in Ghana: Directions in development*. Washington, DC: World Bank. https://doi.org/10.1596/978-1-4648-0941-5

Huber, M., & Mellace, G. (2014). Testing exclusion restrictions and additive separability in sample selection models. *Empirical Economics*, *47*(1), 75–92.

Hung, C. Y. (2008). Overeducation and undereducation in Taiwan. *Journal of Asian Economics*, *19*, 125–137.

International Labour Office (ILO) (2012). *International Standard Classification of Occupations 2008 (ISCO-08): Structure, group definitions and correspondence tables*. Geneva: Author.

International Labour Office (ILO) (2014). *Skills mismatch in Europe: Statistics brief*. Geneva: Author.

Kalfa, E., & Piracha, M. (2017). Immigrants' educational mismatch and the penalty of over-education. *Education Economics*, *25*(5), 462–481.

Kiker, B. F., Santos, M. C., & de Oliveira, M. M. (1997). Overeducation and undereducation: Evidence for Portugal. *Economics of Education Review*, *16*(2), 111–125.

Korpi, T., & Tåhlin, M. (2009). Educational mismatch, wages, and wage growth: Overeducation in Sweden, 1974–2000. *Labour Economics*, *16*(2), 183–193.

Leuven, E., & Oosterbeek, H. (2011). Overeducation and mismatch in the labor market. *Handbook of the Economics of Education*, *4*, 283–326.

Mateos-Romero, L., & Salinas-Jiménez, M. D. M. (2017). Skills heterogeneity among graduate workers: Real and apparent overeducation in the Spanish labor market. *Social Indicators Research*, *132*(3), 1247–1264.

McGuinness, S. (2006). Overeducation in the labour market. *Journal of Economic Surveys*, *20*, 387–418.

McGuinness, S., Pouliakas, K., & Redmond, P. (2018). Skills mismatch: Concepts, measurement and policy approaches. *Journal of Economic Surveys*, *32*(4), 985–1015. https://doi.org/10.1111/joes.12254

Meghir, C., & Palme, M. (1999). *Assessing the effect of schooling on earnings using social experiment* (Institute for Fiscal Studies Working Paper 99/10).

Mehta, A., Felipe, J., Quising, P., & Camingue, S. (2011). Overeducation in developing economies: How can we test for it, and what does it mean? *Economics of Education Review*, *30*(6), 1334–1347.

Mishra, K., & Sam, A. G. (2016). Does women's land ownership promote their empowerment? Empirical evidence from Nepal. *World Development*, *78*, 360–371.

Mulligan, C. B., & Rubinstein, Y. (2008). Selection, investment, and women's relative wages over time. *The Quarterly Journal of Economics*, *123*(3), 1061–1110.

Ng, Y. C. (2001). Overeducation and undereducation and their effect on earnings: Evidence from Hong Kong, 1986–1996. *Pacific Economic Review*, *6*(3), 401–418.

Pagán, J. A. (2002). Gender differences in labor market decisions in rural Guatemala. *Review of Development Economics*, *6*(3), 428–441. doi.org/10.1111/1467-9361.00165

Psacharopoulos, G., & Patrinos, H. A. (2002). *Returns to investment in education: A further update*. Washington, DC: Education Sector Unit, World Bank.

Quinn, M. A., & Rubb, S. (2006). Mexico's labor market: The importance of education-occupation matching on wages and productivity in developing countries. *Economics of Education Review*, *25*(2), 147–156.

Robst, J. (1994). Measurement error and the returns to excess schooling. *Applied Economics Letter*, *1*, 142–144.

Rubb, S. (2003). Overeducation in the labor market: A comment and re-analysis of a meta-analysis. *Economics of Education Review*, *22*, 621–629.

Rubb, S. (2014). Overeducation and earnings within an occupation: Controlling for occupational heterogeneity of nurses. *Education Economics*, *22*(3), 257–269. https://doi.org/10.1080/09645292.2011.631416

Salinas-Jiménez, M. D. M., Rahona-López, M., & Murillo-Huertas, I. P. (2013). Gender wage differentials and educational mismatch: An application to the Spanish case. *Applied Economics*, *45*(30), 4226–4235.

Sloane, P. J., Battu, H., & Seaman, P. T. (1999). Overeducation, undereducation and the British labour market. *Applied Economics*, *31*(11), 1437–1453. https://doi.org/10.1080/000368499323319

Thurow, L. C. (1975). *Generating inequality*. New York: Basic Books.

UNESCO Institute for Statistics (2012). *International standard classification of education: ISCED 2011*. Montreal: Author.

Verdugo, R. R., & Verdugo, N. T. (1989). The impact of surplus schooling on earnings: Some additional findings. *Journal of human resources*, 629–643.

Verhaest, D., & Omey, E. (2006). The impact of overeducation and its measurement. *Social Indicators Research*, *77*(3), 419–448.

Verhaest, D., & Omey, E. (2009). Objective over-education and worker well-being: A shadow price approach. *Journal of Economic Psychology*, *30*(3), 469–481.

Verhaest, D., & Omey, E. (2012). Overeducation, undereducation and earnings: Further evidence on the importance of ability and measurement error bias. *Journal of Labor Research*, *33*, 76–90.

Wilcox, R. (2005). Kolmogorov-Smirnov test. *Encyclopedia of Biostatistics*. doi: 10.1002/ 0470011815.b2a15064

World Bank (2004). *Books, building and learning outcomes: An impact evaluation of World Bank support to basic education in Ghana*. Washington, DC: Author.

Yeo, J. Z., & Maani, S. A. (2017). Educational mismatches and earnings in the New Zealand labour market. *New Zealand Economic Papers*, *51*(1), 28–48.

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APPENDIX

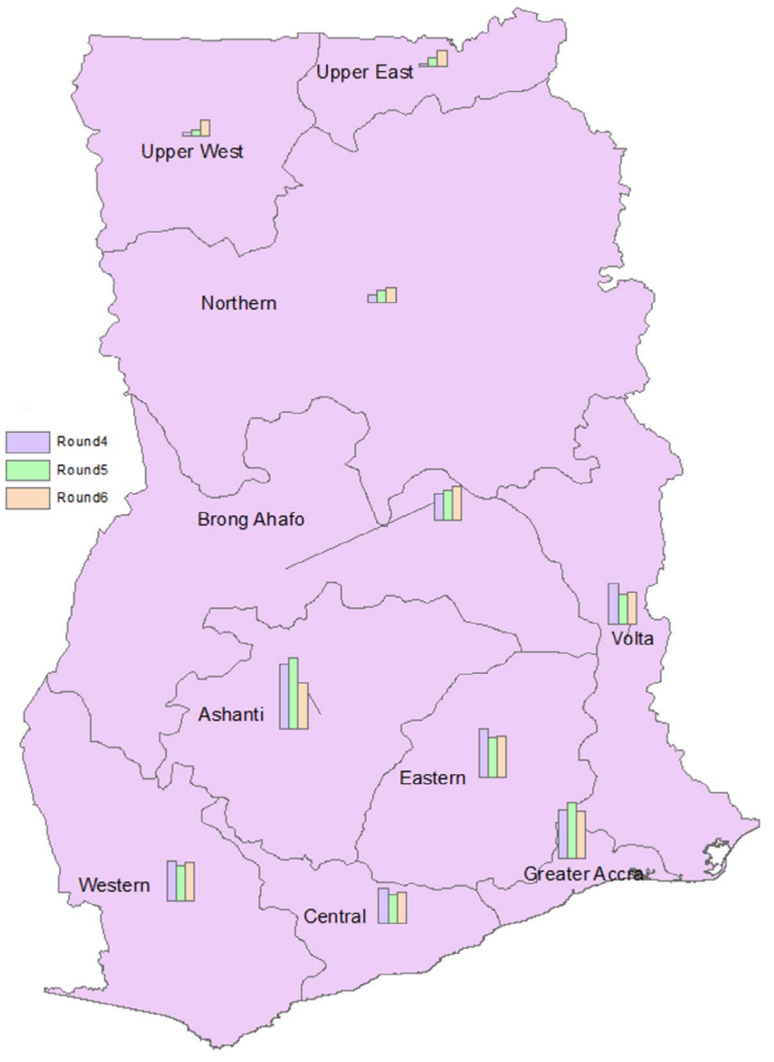

FIGURE A1 Regional distribution of the sample

TABLE A1 Summary statistics

	Pooled			Men			Women		
	N	Mean	S.D.	*N*	Mean	S.D.	*N*	Mean	S.D.
Full sample									
Employment status: Currently employed	26,456	0.85	0.36	14,375	0.89	0.32	12,081	0.80	0.40
Employment status: Currently not employed	26,456	0.15	0.36	14,375	0.11	0.32	12,081	0.20	0.40
Age (years)	26,456	38.63	9.68	14,375	39.24	9.78	12,081	37.92	9.51
Men	26,456	0.54	0.50						
Women	26,456	0.46	0.50						
Married	26,456	0.61	0.49	14,375	0.64	0.48	12,081	0.58	0.49
Other: Married	26,456	0.28	0.45	14,375	0.23	0.42	12,081	0.34	0.47
Never married	26,456	0.11	0.31	14,375	0.13	0.34	12,081	0.08	0.27
Round 4 (1998–1999)	26,456	0.21	0.40	14,375	0.20	0.40	12,081	0.22	0.41
Round 5 (2005–2006)	26,456	0.26	0.44	14,375	0.27	0.45	12,081	0.25	0.43
Round 6 (2012–2013)	26,456	0.53	0.50	14,375	0.53	0.50	12,081	0.53	0.50
Rural location	26,456	0.47	0.50	14,375	0.51	0.50	12,081	0.42	0.49
Urban location	26,456	0.53	0.50	14,375	0.49	0.50	12,081	0.58	0.49
Employed subsample									
Log of weekly earnings (in Ghana cedis)	18,848	2.94	1.60	10,612	3.06	1.63	8,236	2.79	1.54
Required education (years)	22,254	10.72	2.85	12,591	10.83	3.00	9,663	10.59	2.63
Overeducation (years)	22,254	0.73	2.05	12,591	0.91	2.27	9,663	0.51	1.70
Undereducation (years)	22,254	2.05	3.00	12,591	1.75	2.86	9,663	2.44	3.12
Experience	22,410	23.75	10.40	12,711	23.63	10.41	9,699	23.90	10.39
Hours worked per week	22,098	43.84	20.10	12,533	45.45	19.60	9,565	41.73	20.55

(Continues)

TABLE A1 (Continued)

	Pooled			Men			Women		
	N	Mean	S.D.	*N*	Mean	S.D.	*N*	Mean	S.D.
Men	22,436	0.57	0.50						
Women	22,436	0.43	0.50						
Married	22,434	0.63	0.48	12,732	0.67	0.47	9,702	0.59	0.49
Other: Married	22,434	0.28	0.45	12,732	0.22	0.42	9,702	0.34	0.48
Never married	22,434	0.09	0.29	12,732	0.11	0.31	9,702	0.07	0.25
Managers	22,280	0.11	0.31	12,613	0.12	0.32	9,667	0.10	0.30
Professionals, senior officials, legislators	22,280	0.07	0.25	12,613	0.08	0.27	9,667	0.05	0.23
Technicians, associate professionals	22,280	0.05	0.22	12,613	0.05	0.22	9,667	0.05	0.21
Clerks	22,280	0.02	0.13	12,613	0.02	0.13	9,667	0.02	0.13
Service and sales	22,280	0.20	0.40	12,613	0.09	0.29	9,667	0.34	0.47
Skilled agriculture	22,280	0.30	0.46	12,613	0.35	0.48	9,667	0.24	0.43
Craft and related workers	22,280	0.13	0.34	12,613	0.13	0.34	9,667	0.13	0.33
Plant and machine operators	22,280	0.05	0.22	12,613	0.09	0.29	9,667	0.00	0.06
Elementary occupations	22,280	0.08	0.26	12,613	0.07	0.26	9,667	0.08	0.27
Round 4 (1998–1999)	22,436	0.20	0.40	12,733	0.19	0.39	9,703	0.22	0.41
Round 5 (2005–2006)	22,436	0.27	0.44	12,733	0.28	0.45	9,703	0.25	0.44
Round 6 (2012–2013)	22,436	0.53	0.50	12,733	0.53	0.50	9,703	0.53	0.50
Rural location	22,436	0.49	0.50	12,733	0.53	0.50	9,703	0.45	0.50
Urban location	22,436	0.51	0.50	12,733	0.47	0.50	9,703	0.55	0.50
Self-employment	22,402	0.36	0.48	12,721	0.21	0.41	9,681	0.56	0.50
Wage workers	22,402	0.29	0.46	12,721	0.38	0.49	9,681	0.18	0.38
Agriculture	22,402	0.34	0.48	12,721	0.41	0.49	9,681	0.26	0.44

Note: S.D. = standard deviation; only individuals who responded "Yes" to question asked about whether they have ever attended school were included in the construction of the education variables.

TABLE A2 Description of variables

Variable	Description
ln y	Log of weekly earnings in Ghana cedis
Employed	Dummy variable: 1 if individual is currently employed, 0 if not currently employed
Required education	Number of years of required education in the major occupation group where the individual is employed
Overeducation	Number of years of education above the modal number of years of education in the major occupation group where the individual is employed
Undereducation	Number of years of education below the modal number of years of education in the major occupation group where the individual is employed
Education match	Index measure of education match. Ranges from 0 to 1
Experience	Years of potential experience
Experience squared	Years of experience squared
Hours of work	Number of hours worked per week
Female	Dummy variable: 1 if female, 0 if male
IMR (lambda)	Inverse Mills ratio, derived from participation equation
Location	Dummy variable: 1 if urban area, 0 if rural
Marital status: Other	Dummy variable: 1 if other, 0 if married
Marital status: Never married	Dummy variable: 1 if never married, 0 if married
Region	Dummy variables for the 10 regions (Central, Western, Greater Accra, Volta, Eastern, Ashanti, Brong Ahafo, Northern, Upper East, Upper West)
Occupation	Dummy variables for the nine occupational groups
Wage employment	Dummy variable: 1 if wage employment, 0 if self-employment
Agriculture	Dummy variable: 1 if employed in agriculture, 0 if self-employment
Urban	Dummy variable: 1 if individual resides in an urban area, 0 if rural
Round 5	Dummy variable: 1 if survey round is 5, 0 if survey round is 4
Round 6	Dummy variable: 1 if survey round is 6, 0 if survey round is 4

TABLE A3 Effects of educational mismatch on earnings using match between individual educational attainment and required education for their occupation

DV: Log of weekly earnings	(1) Pooled	(2) Men	(3) Women
Undereducated	−0.214***	−0.188***	−0.218***
	(0.0197)	(0.0258)	(0.0303)
Overeducated	0.221***	0.181***	0.239***
	(0.0233)	(0.0286)	(0.0401)
Female	−0.380***		
	(0.0178)		
Marital status: Other	−0.138***	−0.2346***	−0.0519**
	(0.0155)	(0.0220)	(0.0224)
Marital status: Never married	−0.318***	−0.464***	−0.1633***
	(0.0307)	(0.0411)	(0.0490)
Experience	0.0068**	0.0077**	0.0052
	(0.0030)	(0.0021)	(0.0044)
Experience squared	−0.0001	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)
Hours of work	0.0036***	0.0026***	0.0042***
	(0.0004)	(0.0005)	(0.0005)
Round 5	1.366***	1.4587***	1.215***
	(0.0220)	(0.0296)	(0.0393)
Round 6	2.835***	2.968***	2.626***
	(0.0234)	(0.0301)	(0.0424)
Wage employment	−0.0548***	−0.146***	0.0270
	(0.0201)	(0.0267)	(0.0337)
Agriculture	−0.828***	−0.922***	−0.701***
	(0.0314)	(0.0464)	(0.0489)
IMR (lambda)	0.167***	0.196**	0.079
	(0.0639)	(0.0892)	(0.0812)
Rho	0.183	0.223	0.085
Sigma	0.914	0.929	0.930
Location FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes
R-squared	0.67	0.68	0.65
Observations	18,357	10,279	8,078

Note: Robust standard errors in parentheses.

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.