LUND UNIVERSITY

SCHOOL OF ECONOMICS AND MANAGEMENT

# SKILL RETURNS AND LABOR MARKET MISMATCHES

## EXPLORING WORKFORCE POTENTIAL IN URBAN GHANA AND KENYA

*Abstract*

Ghana and Kenya have both made significant efforts to strengthen the skills profile of their young and growing workforces. Raising skill levels and matching workers correctly to jobs is believed to increase productivity and reduce unemployment. The purpose of this thesis is to explore the skills potential within the urban workforces of Ghana and Kenya using data from the Skills Towards Employment and Productivity (STEP) measurement program. In order to encircle unexploited potential, present skills and educational mismatches were mapped out and described. The profitability of skills investments was predicted by estimating the wage returns and occupational opportunities associated with each skill domain using ordinary least squares (OLS) and probability regressions. The study found that Ghana had a higher employment rate than Kenya, but a larger number of mismatched workers in terms of education. While the Ghanaian workers generally had higher education than what was required at their jobs, mismatched Kenyans generally worked below the job's requirements. In both countries, workers reported an underutilization of cognitive and computer skills. The results also showed that schooling, computer skills and solving & learning abilities predicted higher earnings and labor market opportunities, while personality traits and cognitive skills generally were not rewarded in the labor market.

*Keywords: skill returns, labor market mismatches, Kenya, Ghana, STEP, human capital*

**EKHS21**
**Master Thesis, First Year (15 credits ECTS)**
**May 2022**
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**Examiner:** Jonas Helgertz
**Word count:** 11151

## Acknowledgements

I would like to thank my supervisor Jutta Bolt for providing useful feedback and encouraging me to improve this research. I would also like to express gratitude towards my fellow classmates for many helpful thoughts and discussions, and not least company throughout the thesis writing process. Lastly, I would like to thank my closest friends and family, and especially my partner Jacob, for showing infinite patience and encouraging me along the way. Thank you for your invaluable support.

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# List of Abbreviations

**DTDA** – Danish Trade Union Development Agency
**GDP** – Gross Domestic Product
**ILO** – International Labor Organization
**IMF** – International Monetary Fund
**ISCED** – International Standard Classification of Education
**ISCO** – International Standard Classification of Occupations
**QIES** – Quarterly Informal Economy Survey
**STEP** – Skills Towards Employment and Productivity
**TVET** – Technical Vocational Education and Training

# 1 | Introduction

Throughout decades of thought about the economics of human capital, economists have often had a very simplified view of skills. Traditionally, the literature on wages and other labor market outcomes have focused on the aspects of education and experience, while more recent literature emphasizes that people can acquire more or less skills in life than those directly associated with education (Hanushek & Woessmann, 2008; Johanson & Adams, 2004). This is particularly apparent in Sub-Saharan Africa, where a large number of graduates lack basic literacy and numeracy skills despite substantial investments in education (Morsy & Mukasa, 2019; Johanson & Adams, 2004). In a report from 2019, the World Bank called for 'system-wide change' and 'smart skills development strategies' after diagnosing the Sub-Saharan African workforce to be the least skilled in the world (Arias *et al*., 2019).

As seen from the Sub-Saharan African case, skills are not always guaranteed from education (Darvas & Palmer, 2014; Johanson & Adams, 2004). The increasing emphasis on skills and people-driven development strategies seen across the region marks an important step away from the traditional focus on formal education. Instead, ability differentials have gained more interest among researchers. Being closely related to productivity, ability serves as a more relevant determinant of promotion prospects or earnings potential (Heineck & Anger, 2010).

Although higher education and skills attainment are predicted to make job-seekers attractive for higher-skilled jobs, there are several holdbacks to reaching full earnings potential. A considerable amount of literature highlights the various micro and macro implications of imperfect matching of employees to job positions (Morsy & Mukasa, 2019). Mismatches arising from an individual working below their level of education or skill are both theoretically and empirically predicted to have adverse effects on earnings, job satisfaction and labor force productivity (Allen & De Weert, 2007).

Despite human capital being a well-established doctrine within economic history, existing literature on labor market mismatches and earnings is skewed towards developed countries and has a predominant focus on education. The purpose of this paper is to take a multidimensional approach to skills and shed light on skill mismatches and returns in Sub-Saharan Africa. Extensive skills data provided by the World Bank's skills measurement program for Ghana and Kenya not only enables an East-West comparison within Africa, but expands the coverage of skills and mismatch research on the developing world. More specifically, this thesis is guided by the following two questions:

*(1) To what extent are there unexploited skills in the Kenyan & Ghanian workforce?*

*(2) Which skills generate the best earnings and occupational opportunities?*

Raising the range and level of skills is believed to expand employment and increase productivity in strategic economic sectors (Darwas & Palmer, 2014). However, the foundation for any skills improvement agenda relies on being able to identify the needs of the current skills profile (Darvas *et al*., 2017). Both Ghana and Kenya have adopted educational strategies focusing on strengthening the skills profile of their young and growing labor forces (Balwanz, 2012; IMF, 2012). Yet, high unemployment rates continue to persist and their skills development strategies are criticized for being inefficient and misdirected (DTDA, 2020; ILO, 2020; Kissi *et al*., 2020). The mapping of skills attainment, unused skills and economically favorable skills will help encircle where profitable investments should be made.

The content of the thesis is organized in the following manner. Section 2 provides contextual insight to the economies of Ghana and Kenya by describing their economic and labor market background as well as future challenges. Section 3 presents a theoretical framework comprising three established theories on human capital and labor market matching, followed by previous research on skills returns and mismatches in section 4. The methodology, data and methods are explained in detail in section 5, while section 6 describes and lays out the main results. Section 7 sorts and discusses the results from the previous section with regards to the theory and literature. The last and eighth section concludes the analysis and summarizes the implications of this thesis for current and future development.

# 2 | Contextual Background

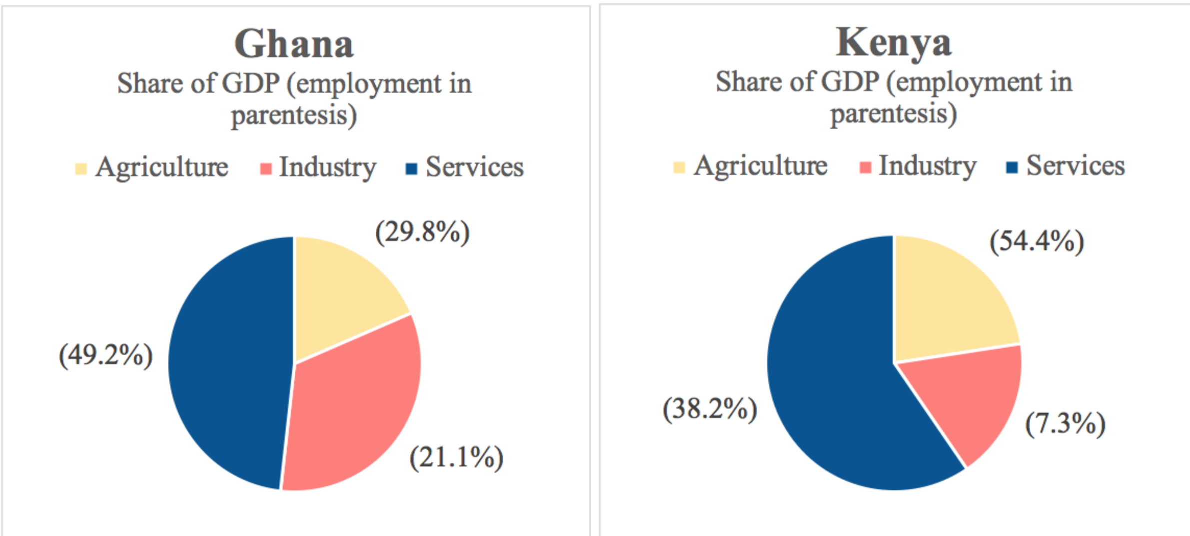
This section aims to give contextual insight on the two economies of Ghana and Kenya. Describing their economic and labor market profiles will help illustrate the countries' current status from which this thesis takes off, as well as encircle the challenges facing them going forward. Section 2.1 describes similarities and differences of Ghana's and Kenya's stories of economic growth since the turn of the century, while sections 2.2 and 2.3 address two prominent labor market challenges represented by the youth bulge on the one hand, and the dominance of the informal sector on the other. The last subsection is concerned with skills development initiatives and the approaches taken by the government to tackle the above challenges.

## 2.1 The Economic Record of Ghana and Kenya

In the 21th century, Ghana has achieved significant and sustained economic growth fueled mainly by strong price increases of their main commodity exports (gold and cocoa) (Honorati & Johansson de Silva, 2016). The country's record of more than 20 years of stable positive GDP per capita growth (World Bank, 2022) has brought several improvements in living standards. By 2007, the country joined the ranks of middle income countries and by 2013, Ghana reached the first Millennium Development Goal in 2013 by halving poverty from the 1992 rate of 51% to 24% (Baah-Boateng, 2016). The significant poverty reduction, rising incomes and increasing productivity has further led to rapid urbanization with rural migrants being able to take part in more productive sectors of the economy (Darvas *et al*., 2017).

The market reforms introduced in the early 2000s accelerated economic growth also in Kenya. Despite several episodes of stagnant growth in the last half of the 20th century, Kenya has grown to be one of the largest economies in the East African Region (Adams *et al*., 2013; Omolo, 2010). Investments in tourism and the expansion of innovative services, such as mobile communication and financial intermediation, have been identified to be the primary contributors to Kenya's economic growth. As a result of increasing demand for services and trade, public resources were allocated towards social infrastructure, transport and educational services, largely benefiting the population of Kenya (Adams *et al*., 2013).

Although both countries have seen significant improvements in economic performance and living standards, the primary cause of growth can be attributed to different parts in the economy across Ghana and Kenya. Figures 2.1 and 2.2 demonstrate a snapshot of the 2019 sectoral composition in GDP with the total employment per sector added in parentheses.



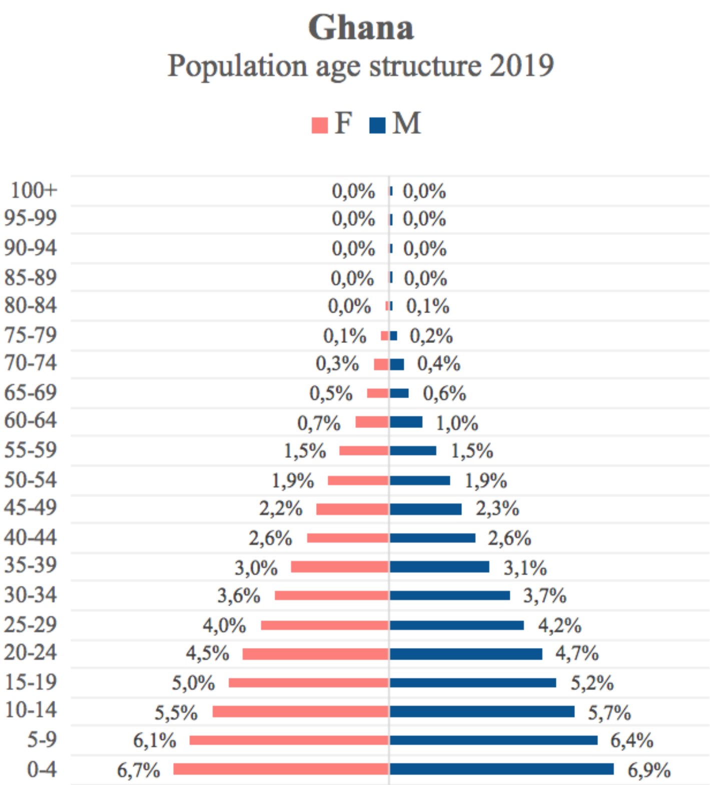

***Figures 2.1 & 2.2:*** *Share of economic sectors in GDP with share of total employment per sector in parenthesis (2019). Source: Statista (2022a, 2022b, 2022c, 2022d)*

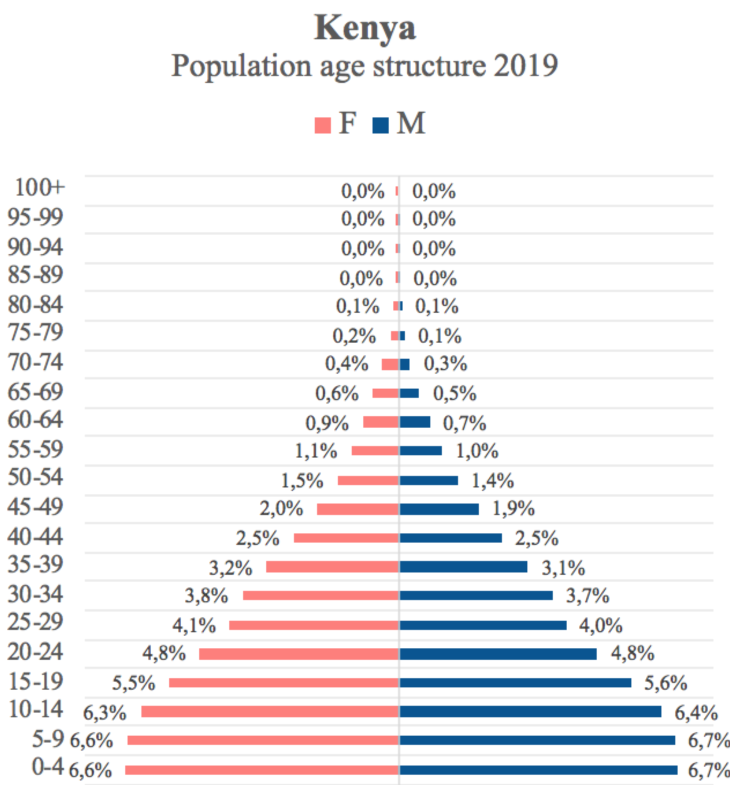
Compared to Ghana, the economy of Kenya had a lower share of employment in the service sector at the same time as services comprised a larger share of total GDP. Thus, Kenya's service sector was more productive relative to Ghana. A corresponding relative distribution was found for Ghana's industry sector, which was more efficient in relation to Kenya's. The agricultural contribution to GDP is quite similar across both countries. However, agricultural activities employ less than a third of Ghana's workers but more than half of Kenya's, indicating a higher productivity in Ghana's agricultural sector.

## 2.2 Harnessing the Demographic Dividend

Despite high growth rates and impressive progress, the labor market of Ghana, Kenya and many other Sub-Saharan African economies face economic and social challenges associated with a growing population. As the share of the productive population is increasing in the total economy, there is a growing need to provide productive and sufficient employment opportunities for all. This is highly relevant in order to make economic use of the productive potential within the youth demographic and keep unemployment at bay (Singh & Kumar, 2021).

With a population count increasing by about a million people a year, Kenya's youth (ages 15-29) make up as much as 29% of the total population. The corresponding number for Ghana is 28% (PopulationPyramid, 2022a; 2022b). Observing the age structures more closely, the triangular shapes seen in figures 2.3 and 2.4 indicate the presence of a young population. For reference, the population structure in Western Europe has a more balanced, 'box-shaped', distribution of youth, adults and elderly across the population with only a 17% share of 15-29 year olds in the total population (PopulationPyramid, 2022c)




***Figures 2.3 & 2.4:*** *The age structure of Ghana's and Kenya's population in 2019 showing the share of each age cohort in the total population. Source: PopulationPyramid (2022a; 2022b)*

To meet the needs of the increasing proportion of workers entering the labor force each year; employment, and the lack thereof, are important political and socio-economic challenges facing policy makers in Ghana and Kenya (Otoo *et al*., 2009). The growing young population represents great social and economic opportunities, but also poses large challenges. This is for example apparent in Kenya. By having one of the highest youth unemployment figures in the world, job creation lies in the forefront of Kenya's most urgent challenges for economic growth and development (Franz & Omolo, 2014; Were, 2017).

## 2.3 The role of (In)formality of Employment

The informality of employment relationships is one of the main features of both Ghana's and Kenya's labor markets. Compared to the formal sector, business and labor regulations are not always applied in practice, including pension and minimum wage schemes (DTDA, 2020). Around 90% of Ghana's workers over the age of 15 work in low-value service activities within the informal economy, and more than half of all Ghanaian adults are self-employed (Ghana Statistical Service, 2016; Otoo *et al*., 2009). In addition, a large proportion of workers in wage employment lack formal contracts. Accordingly, these workers become non-liable for taxes and difficult to encompass in legal and social protection provisions (Otoo *et al*., 2009).

Generally, economic reforms make slow progress in Ghana where many law reforms on the labor market are neither approved nor followed according to international standards. Thus, the large share of informal employment is not merely a result of insufficient job creation, but also the lack of inherent incentives to formalize informal activities (DTDA, 2020).

Similar to Ghana, the vast majority of Kenyan job-seekers end up in the informal sector. Common jobs are for example within manufacturing, hospitality and trade (Adams *et al*., 2013). Kenya has been characterized as having a dual economy, where formal jobs dominate the high-productivity and high-growth sectors, but stand for relatively little job creation. For reference, the informal sector makes up around a third of Kenya's total GDP while it employs more than 80% of workers (QIES, 2022; Statista, 2022e).

The growing share of informal employment has further increased uncertainty for Kenyan workers in terms of predictability of employment and securing a decent livelihood (Balwanz, 2012). Although casual relationships between employers and workers are more common within the informal sector, they are also found in formal employment. Casual employment complicates partaking in the fundamental rights of workers, such as freedom of association, right to paid leave and right to social protection. All together contrasting with the country's desire to strengthen social protection and reduce poverty (Omolo, 2010).

## 2.4. Skill Initiatives and Investments

Skills and education are important determinants of increasing productive capacity and the number of productive jobs. They are also strongly related to earnings potential and labor market opportunities. Although Ghana has seen increases in educational enrolment, completion rates and access to formal education, the quality of learning has not followed a similar pattern. In fact, a majority of students leave basic education with insufficient literacy and numeracy skills. Very few also get the chance to improve or complement their set of skills through second chance programs as they are needed for housework, agriculture or street peddling (Darvas &  Palmer, 2014).

Education and skills development are also addressed in Kenya's long-term development plan – *Kenya Vision 2030*. In addition to paving the way into the labor market, skills development aims to help mitigate the risk of unemployment, poverty, marginalization and impediments to welfare services access facing the Kenyan youth (Balwanz, 2012; Hope, 2012; ILO, 2019). But like in Ghana, many students are dropping out or graduating with inadequate skills for employment. The most common reasons being poverty, inappropriate facilities and high costs of education. Pregnancy and cultural practices like early marriage are additional pressures especially affecting female attainment in education (Wamuyu Muthee, 2010).

In terms of job opportunities, few graduates transition successfully between school and higher skilled jobs. In Ghana, entering a low productivity job after school continues to be the main destination for Ghanaian school leavers, especially for girls (Honorati & Johansson de Silva, 2016; Palmer, 2007). These prospects present few incentives for youth in Ghana and Kenya to invest in schooling and keep maintaining the gap between individuals in higher-skilled jobs and individuals stuck in lower-skilled jobs (Darvas & Palmer, 2014).

When addressing educational shortcomings, unemployment and the challenges represented by the youth bulge, the governments of both Ghana and Kenya have paid significant attention to post-basic education and vocational training (Balwanz, 2012; Kissi *et al*., 2020). For example, National Employment Policies in Ghana have focused on increasing the integration of technical and vocational education and training (TVET) in the educational system to increase job creation and self-reliance among Ghana's youth (Kissi *et al*., 2020). Similarly in Kenya, the launch of skill development programs and initiatives to expand post-basic education has aimed to complement the regular educational system and facilitate school-to-job transitions (Balwanz, 2012).

However, outcomes have been far from optimal. Due to haphazardly deployed TVET policies (Kissi *et al*., 2020) and low degrees of workplace formalization (DTDA, 2020), joblessness, high informal employment and skills mismatches continue to persist in Ghana. Moreover, authors of several policy and prescriptive papers have expressed concerns about the organization of Kenya's skills development. Most frequent are lack of coordination (ILO, 2020), inability to match skills supply with demand (Hope, 2012), fragmented legislation and governance for skills programs (ILO, 2020), and absence of youth-specific policies for skills upgrading (Wamuyu Muthee, 2010).

# 3 | Theoretical Framework

No attempt has yet been made to formulate a unified theory on education and skills mismatch (Quintini, 2011). Nevertheless, the scope of this thesis tangents to several strands of literature on job and skills mismatch that are useful for understanding the economic implications from skill imbalances. The most relevant are *Human Capital Theory* that focuses on the labor supply for understanding productivity and earnings; *Signaling Theory* emphasizing the demand side; and *Assignment Theory* that takes the middle ground.

## 3.1 Human Capital Theory

A dominant paradigm in economics of education is human capital theory (e.g. Becker, 1962, 1964; Mincer, 1974; Schultz, 1961). The early human capital theorists argued that skills and knowledge were of equal or even greater importance for creating economic growth compared to the traditionally considered factors of labor, physical capital or land. In essence, human capital theory focuses on the productivity-enhancing effects stemming from training and educational investments in people, where more productive individuals are more employable and enjoy higher earnings (Carneiro *et al*., 2010). But as with physical capital, there are little returns without investment.

For the individual, human capital investments are associated with both direct costs (e.g. tuition fees) and indirect costs (e.g. renounced earnings while in school or training). The returns to investment for an individual are then most commonly measured by the net gain in lifetime earnings resulting from their educational or skills accumulation (illustrated in figure 3.1). Schultz (1961) emphasized that people will make large efforts and pay considerable costs of skill accumulation in order to obtain higher returns in the form of a better job, higher pay or more favorable working conditions. Thus suggesting that an increase in skills or education would be positively associated with an increase in income.

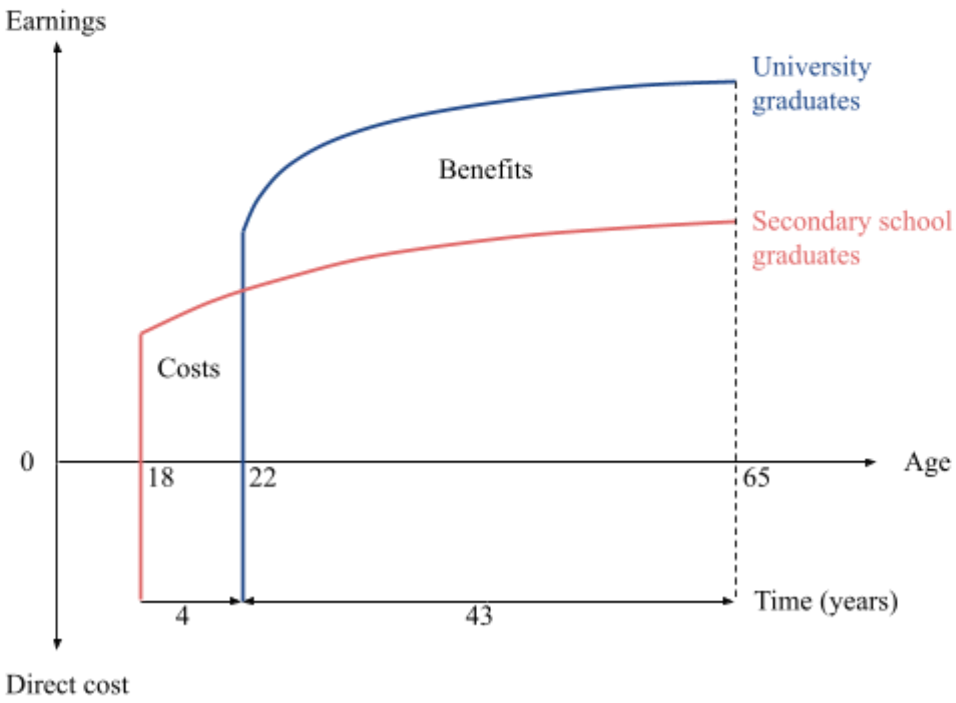



***Figure 3.1:*** *A typical age-earnings profile by level of education*

The theory of human capital assumes that workers are always optimally allocated on the labor market given their human capital stock. Accordingly, the theory does not consider an overskilled or overeducated workforce as more than a temporary deviation from equilibrium (Morsy & Mukasa, 2019). Short-term mismatches will induce an adjustment back to equilibrium where either employers will make better use of available skills to saturate productivity, or workers will look for a more appropriate job match to realize their productive potential and increase their earnings (Desjardins & Rubenson, 2011).

## 3.2 Signaling Theory

This theory assumes asymmetric information between actors in the labor market, where the employer lacks information about the skills of their potential employees (Arrow, 1973; Spence, 1973; Stigler, 1961). Signaling theory (e.g. Arrow, 1973; Riley, 1976; Spence, 1973; Weiss, 1995) views educational credentials as a way to signal probabilistic information about the worker to the employer. In contrast to human capital theory, the signaling model allows employers to draw assumptions about an individual's unobserved characteristics given their qualifications (Weiss, 1995).

Signaling mechanisms are important to consider since employers rarely use direct skills measurements of their applicants to assess their literacy or numeracy proficiency (Desjardins & Rubenson, 2011). These mechanisms also affect the perception of skills requirements. For example, the phenomenon of 'qualification inflation' arises when firms no longer are satisfied with the abilities that come with a certain required level of education. When the higher ability individuals cannot be singled out by educational qualification, firms are likely to raise their educational requirements despite unchanged job tasks (Quintini, 2011).

This qualification inflation induces qualification mismatches when there is in fact no underlying skill mismatch. Considering the signaling mechanisms and the fluctuation of skills perception, this theory acknowledges that actual skills may be rewarded above or below the signaling effects of education.

### 3.3 Assignment Theory

Assignment theory (e.g. Hartog, 1986; Sattinger, 1993) provides an 'in-between' framework to human capital theory and signaling theory, where both individual and job characteristics are considered the main determinants of productivity and earnings. The matching mechanism of the model suggests an ideal where the highest skilled individuals are assigned the highest skilled jobs, moving from the top down to the lowest skilled jobs and individuals (Desjardins & Rubenson, 2011). The theory agrees with the productivity returns of education, but acknowledges that the characteristics of the job are equally important. A high-skill job match pays best, but when earnings are more closely tied to sector or job than the worker it is ambiguous whether overskilled or underskilled workers earn more.

This theory contrasts to human capital theory in two important ways. First, it describes a more dynamic labor market where both the supply and demand side of labor are relevant for earnings and productivity, rather than the long run supply of labor only. Second, it accounts for worker and firm heterogeneity and thus more effectively describes the match between job and worker. By recognizing that the employer does not necessarily adjust their demand in accordance with the available skill supply, assignment theory allows for a persistence in skill and educational mismatches on the labor market (Desjardins & Rubenson, 2011).

## 4 | Literature Review

### 4.1 Labor Market Mismatches and their Consequences

The phenomenon of skill or educational mismatch occurs when an employee possesses either more or less skills or education than what is required for their job (De Vreyer & Roubaud, 2013). Mismatches signal a likely suboptimal allocation of skills and educational qualification across jobs with effects on both micro and macro levels (Morsy & Mukasa, 2019). It is however difficult to disentangle from the literature whether there are differences in outcomes between mismatches in education and mismatches in skills. This section will attempt to distinguish between the two and review the existing literature on mismatches on the labor market.

In the economic literature on mismatch, the research primarily focuses on the effects of working a job that does not match the obtained level of education. This typically goes with an assumption that there is simultaneously a mismatch between acquired and required skills. For example, assignment theory equalizes educational and skills mismatches (Allen & van der

Velden, 2001). A few papers show and recognize that educational and skill mismatches indeed are related but that a mismatch in one does not necessarily imply a mismatch in the other (Allen & De Weert, 2007; Allen & Van der Velden, 2001; Badillo-Amador *et al*., 2012; Badillo-Amador & Vila, 2013; Carneiro *et al*., 2010; Green & McIntosh, 2007).

A relevant aspect in the nexus between mismatch and labor market outcomes is job satisfaction as it influences worker productivity and the likelihood of changing jobs (Alba-Ramirez, 1993; Allen *et al*., 2013; Allen & Van der Velden, 2001; Rubb, 2006; Sicherman, 1991). Several studies have confirmed a negative correlation between educational mismatch and job satisfaction. Battu *et al*. (1999) and Belfield & Harris (2002) find that currently or previously matched workers report significantly higher levels of job satisfaction. Perceived overqualification (Johnson & Johnson, 2000) and mediation factors like wage, health status and other observable job characteristics (Fabra Florit & Vila Lladosa, 2007) are further recognized determinants.

A number of studies also find that skill mismatches are a much better predictor of job (dis)satisfaction than educational mismatches, likely because the effects of the former allow for more unobserved worker heterogeneity (Badillo Amador, 2011; Allen & van der Velden 2001; Morsy & Mukasa, 2019). For a sample of youth in 10 African countries, Morsy & Mukasa (2019, 2021) found that education- and skill-mismatched individuals were more likely to search for a new job compared to those who were better matched. They also conclude that skill and educational mismatches were rather persistent over time and that the probability of getting a better educational match increased with educational level.

There are also economic implications of skill and educational mismatches. A few dynamics where there is broad consensus can be singled out from the quite extensive body of literature concerned with mismatches and wage:

- Overeducated workers suffer a wage penalty compared to matched workers with the same level of education (Bauer, 2002; Chevalier & Lindley, 2009; Duncan & Hoffman, 1981; Groot, 1996; Hartog, 2000; Morsy & Mukasa, 2019; Sicherman, 1991; Verdugo & Verdugo, 1989)
- Undereducated workers enjoy a wage premium compared to matched workers with the same level of education (Bauer, 2002; Hartog, 2000; Morsy & Mukasa, 2019, 2020; Sicherman, 1991; Verdugo & Verdugo, 1989)
- The wage effects of overeducated workers are stronger than the effects of undereducation (Bauer, 2002; Hartog, 2000; Verdugo & Verdugo, 1989; Badillo-Amador & Vila, 2013)
- Underutilization of skills (being ‘overskilled’) has a negative effect on wages (Allen, *et al.*, 2013; Allen & Van der Velden, 2001; Badillo‐Amador & Vila, 2013; Green *et al*., 2002)

Most of the literature concerned with the effects of mismatches on earnings is focused on higher-income countries. Hence, the paper by Carmichael *et al*. (2021) examining under- and overeducation in Ghana and Kenya deserves particular attention. Concluding that overeducated workers are rewarded above matched workers and that undereducated workers are paid over their educational level, they confirm the above pattern also for Kenya and Ghana.

## 4.2 The Returns to Education and Skills

For decades, the study of returns to education dominated the field of research about human capital in economics. The use of Mincer's (1974) earnings equation which estimates logged earnings on years of schooling appears in numerous studies and policy debates (Smith *et al*., 2018). In more recent years, the Mincer equation has received criticism for reducing the diverse dimensions of human capital into mere years of education (Hanushek *et al.*, 2015; Hanushek & Woessmann, 2008). This section will explore the literature concerned with and beyond years of education as a form of human capital and determinant of economic returns.

The literature consistently reports positive economic returns to education for the individual (e.g. Becker, 1964; Blundell *et al*., 2005; Michaelowa, 2000; Psacharopoulos & Patrinos, 2004). However, returns vary across levels of education. Until recently, evidence from developing countries has suggested a higher return at the primary level than at secondary or higher levels of education. However, studies from the early 2000s find that this pattern is slowly changing where the returns to post-primary education in wage employment are significantly surpassing the returns to primary education (Colclough *et al*., 2009)

Yet, people accumulate more abilities over their life course than those directly associated with education. Cognitive skills are one determinant of returns to human capital and refer to the ability to engage in reasoning, understand complex ideas and acquire knowledge (Pierre *et al*., 2014). Numerous studies on the United States find that both higher-order cognitive skills (IQ) and lower-order cognitive skills (reading, mathematics, vocabulary) predict higher wages (Cawley *et al*., 2001; Hanushek & Woessmann, 2008; Murnane *et al*., 2000; Murnane *et al*., 1995). Similar results were also confirmed in other high-income countries such as the OECD (Hanushek *et al*., 2015), the United Kingdom (McIntosh & Vignoles, 2001) and Canada (Finnie, 2002).

Corresponding evidence from developing countries however, is scarce and often outdated. For Latin America, cognitive skills (in particular reading proficiency) proved an important predictor of job quality and earnings in Colombia (Acosta *et al*., 2015), and test scores on vocabulary, verbal fluency and math problem solving were positively related to earnings for urban dwellers in Peru (Diaz *et al.*, 2013). Only a few papers estimate the returns to cognitive skills in Sub-Saharan Africa. In both South Africa and Ghana, computational skills were more important than reading skills in influencing wages (Moll, 1998; Jolliffe, 1998). In Ghana, the returns to cognitive skills were significant for total and off-farm income (Jolliffe, 1998), but ambiguous for business income (Vijverberg, 1999). For Kenya, Knight & Sabot, (1990) and (Boissiere *et al*., 1985) show that for each educational level, workers with higher cognitive achievement earn more than low achievers.

Apart from cognitive skills, there is a growing interest in personality-related skills and their effects on individuals' decisions and outcomes. Social and behavioral skills belong to the non-cognitive skills category and relate to an individual's personality traits. A common organizational structure of personality traits, that is also reflected in the data used in this thesis, is the 'Big Five' taxonomy (Pierre *et al*., 2014) that includes;

- ❖ **Conscientiousness** – Being goal oriented and having a sense of planning and order. It also encompasses the likelihood of following norms and rules
- ❖ **Openness to experience** – Refers to the joy of learning and coming up with new ideas
- ❖ **Neuroticism** (emotional instability) – The tendency to have negative emotions
- ❖ **Agreeableness** – Being social and cooperatively oriented
- ❖ **Extraversion** – Being outgoing and taking forward approaches in social situations

Findings on wage returns to personality traits are heterogenous, with variations across traits, gender and tenure (Heineck & Anger, 2010). Judge *et al*. (1999) find that both intrinsic (job satisfaction) and extrinsic career success (income and occupational status) were positively predicted by conscientiousness. A number of studies agreed that neuroticism was penalized while its opposite (emotional stability) was positively correlated with wage (Judge *et al*., 1999; Mueller & Plug, 2006; Nandi & Nicoletti, 2014; Nyhus & Pons, 2005). Agreeableness is shown to account for the largest gender differentials in earnings in two studies using Dutch and American data respectively (Nyhus & Pons, 2005; Mueller & Plug, 2006). While this trait was associated with lower wages for women, antagonism (the opposite to agreeableness) generated significant earning advantages for men.

The cognitive and non-cognitive skills literature closest in relevance for this thesis comprises a few studies that also use STEP data. On a sample of 7 developing countries, with Kenya being the only representative from Africa, Tognatta *et al*. (2016) examine the role of cognitive and non-cognitive skills for the gender wage gap. Whereas schooling was a stronger predictor of gender wage differentials, their study showed some evidence for the influence of cognitive skills in Kenya. These effects mattered more at the lower end of the wage distribution. Mohammed *et al*. (2021) demonstrate a similar finding for Ghana, where different personality traits were rewarded differently for men and women depending on their form of employment. In particular, agreeable women and not men were rewarded with higher earnings in the formal sector, while conscientious men, but not women, had higher earnings in the informal part of the labor market.

## 4.3 Contribution to the Literature

It is clear that there is little detailed literature on returns to cognitive and non-cognitive skills in developing countries. While data availability surely has explained some of the bias towards developed countries in the past, returns to human capital in developing countries remain to date an available area for further exploration. Research on educational returns and human capital investments also traces far back in economic history and might give an impression of being a saturated area of research. The theory of human capital has expanded to include skill domains beyond educational attainment, but the coverage of research about these domains has not to the same extent. Most urgent is the need for more updated figures across the developing world together with analyses using more nuanced views of human capital.

This thesis will take a multidimensional approach to human capital with the aim to capture the dynamics and impact of a broader skills spectrum. By analyzing both labor market mismatches and skills returns, this thesis will contribute with a broader mapping of the potential, availability and economic implications of skills in African labor markets. Ghana and Kenya are the only African economies surveyed by the Skills Measurement Program, but rarely analyzed together. The inclusion of both will make fuller use of the data and add a dimension of relativity between one Eastern and one Western African country. All together, this thesis will help contribute to the foundation necessary for conclusions on the economic implications of Kenya's and Ghana's current skill situation.

# 5 | Methodology

In order to undertake the practical steps towards answering the research questions, the thesis adopts a quantitative approach. Given the comparative character of the study, regression- and descriptive multivariate analysis are opted over qualitative methods to ensure a higher level of data standardization across the two countries. Despite difficulties to empirically ascertain causality between the components of analysis, the advantages of regression models are their ability to single out statistical significance of dependencies and their magnitudes of influence.

## 5.1 Data

The main data source of this study is the World Bank's STEP (Skills Towards Employment and Productivity) survey database. The STEP measurement program is the first of its kind to generate internationally comparable data on skills in developing countries. It is also the latest available data to enable detailed cross-country comparisons on skills tenure. The survey was collected between 2011 and 2017 through a two-stage randomization process across urban households and individuals, where one adult (15-64 years) from each household was randomly selected as respondent. Several modules are included, covering detailed information on family background, socioeconomic status, employment and different types of skills.

The main variables of interest are three different sets of self-assessed skills. *Reading*, *writing* and *numeracy* represent the cognitive skills category. These variables include whether and to what extent individuals practice their cognitive skills at or outside of work. The second category comprises non-cognitive skills measured by the Big-Five personality traits (*extraversion*, *conscientiousness*, *openness*, *stability* and *agreeableness*). Each trait is measured by a set of questions, e.g. “are you talkative?” (extraversion) or “do you get nervous easily?” (stability). The last category deals with job specific skills for employed individuals where for example interpersonal skills, freedom to organize work and use of technology is assessed.

Both Ghana and Kenya were included in the first wave of the STEP household survey. The survey was collected between 2011 and 2012 in Ghana and one year later in Kenya. A total of 2987 individuals were surveyed in Ghana and 3894 individuals in Kenya. A lower age limit was set to 25 years to ensure that the vast majority of individuals in the sample had the opportunity to complete education by the time the survey was conducted. The final sample is broadly summarized in table 5.1.

**Table 5.1:** Summary table of sample characteristics

| **Sample characteristic** | | **Ghana** | **Kenya** |
|---|---|---|---|
| Sample size | | 2175 | 2479 |
| Percent female | | 57.9 | 51.8 |
| Mean age | | 37.9 | 34.5 |
| Labor market status | Employed | *85.3%* | 74.5% |
| | Unemployed | *4.9%* | 12.8% |
| | Inactive | *9.8%* | 12.7% |

## 5.2 Methods

The first research question deals with whether and to what extent there are skills mismatches in the workforces of Ghana and Kenya. A common way to measure educational mismatches is by comparing the obtained level of education with the required level of education at the job that employs the individual (Morsy & Mukasa, 2019; Carmichael *et al*., 2020; Allen *et al*., 2013; Rubb, 2006). The educational mismatch variable was created using two sources of input. First, the individual’s reported educational attainment translated into the corresponding level of ILO’s International Standard Classification of Education (ISCED) ranging between 1-5, and second; his or her answer to the question “What minimum level of formal education do you think would be required before someone would be able to carry out this work?”. The difference in ISCED levels between obtained education and assessed educational requirement represents their educational match.

A similar approach was used for measuring skills mismatches. This thesis defines skills mismatch using employees’ self-perceived match between possessed skill and the use of that skill on the job. The skill usage outside and on the job were assigned a score between 0=skill not used, and 3=high, where the difference in scores represents their degree of mismatch. The advantage of using self reported values is that job heterogeneity can be taken into account, since the employee likely is the most knowledgeable person about their own job and the skills required to perform their work tasks satisfactorily. Skills mismatches were measured for the four skills variables for which this type of data was available. The skills and educational mismatch variables were then graphically illustrated across the two countries.

The second research question is concerned with the wage returns to skills on the one hand, and occupational opportunities generated by skills on the other. With inspiration from Hampf *et al*. (2017), Mohammed *et al*. (2021) and Hanushek *et al.* (2015), the wage returns was estimated using an augmented Mincerian earnings equation based on the original Mincer's (1974) semi-logarithmic function of human capital earnings:

$$ln\, W = \beta_0 + \beta_1 S + \beta_2 EX + \beta_3 EX^2$$

where *ln W* is the logarithm of earnings and $\beta_1$ represents the average return in earning from an additional year of schooling (*S*). *EX* and are years of labor market experience and $EX^2$ is its squared form. Building upon the Mincer equation, the empirical model in this thesis was estimated as follows:

$$\begin{gathered} ln\, W_i = \beta_0 + \beta_1 S_i + \beta_2 tenure_i + \beta_3 tenure^2_i + \beta_4 cog'_i \\ + \beta_5 personality'_i + \beta_6 jobspecific'_i + \beta_7 C'_i + \varepsilon_i \end{gathered}$$

where $tenure_i$ is the experience variable capturing the individual's occupation-specific experience. The square of *tenure* is included to approximate potential quadratic effects of experience established in earnings studies (Nyhus & Pons, 2005). $Cog_i$ is a vector of the cognitive skills variables, and $personality_i$ and $jobspecific_i$ are vectors representing the personality-related (socio-emotional) and job specific skills variables respectively. $C_i$ signifies the control variables and $\varepsilon_i$ is the error term. Detailed information on the variables within the *cog*, *personality*, and *jobspecific* categories are presented in table 5.2. Gender, age and type of employment (formal/informal) were controlled for.

**Table 5.2:** Description of variables

| Variable | | Variable description | Measurement |
|---|---|---|---|
| **Earnings** | | Hourly wage in USD | Natural logarithm of hourly wage in USD (continuous scale) |
| **Schooling** | | Years of schooling | Years of education actually completed (discrete scale) |
| **Tenure** | | Months spent in current occupation | Number of months since start of current job (discrete scale) |
| **Cognitive skills** | **Reading** | Frequency of reading and length of reading material | Length of material read overall score (0-3)[1] |
| | **Writing** | Frequency of writing and length of written material | Length of material written overall score (0-3) |
| | **Numeracy** | Frequency and level of mathematical skills use | Numeracy overall score (0-3) |
| **Socio-emotional skills** | **Conscientiousness** | Self assessed carefulness, effort and efficiency when doing a job task | Conscientiousness average (1-4)[2] |
| | **Openness to experience** | Self assessed innovativeness, interest in new things and enjoyment of beautiful things | Openness average (1-4) |
| | **Neuroticism** | Self assessed nervousness, stress resistance and likelihood to worry | Neuroticism average (1-4) |
| | **Agreeableness** | Self assessed politeness, generosity and forgiving ability | Agreeable average (1-4) |
| | **Extraversion** | Self assessed likelihood of being talkative, sociable and sharing opinions | Extraversion average (1-4) |
| **Job-relevant skills** | **Interpersonal skills** | Frequency of meeting and/or interacting with people | Contact with people outside of work score (0-3) |
| | **Use of technology** | Frequency of computer use | Frequency of computer use overall score (0-3) |
| | **Autonomy** | Freedom to organize work | Autonomy and repetitiveness at work score (0-3) |
| | **Solving and learning** | Frequency of learning new things and doing tasks that require more than 30 minutes | Frequency of thinking and learning new things score (0-3) |

In terms of occupational opportunity, this thesis defines two aspects; (1) the formality of employment and (2), the skill level associated with each occupation. Being a formal worker has several advantages for the individual. Formal and contractual employment ensures predictability of employment, regulated wage setting and social security, while informal employment usually does not. The monetary and non-monetary benefits offered within the

[1] The maximum value of skills usage at work score and skills use at home score, 0=skill not used; 1=low; 2=medium; 3=high

[2] The average score to the questions of skill usage after reversed scoring, 4=almost always; 3=most of the time; 2=some of the time, 1=almost never

formal sector can naturally be considered desirable outcomes of human capital investments, hence the inclusion of formality in the analysis. Since wages are positively related to skills investments according to human capital theory, a higher-skill occupation is hypothesized to generate higher wages. Thus, a higher skilled occupation theoretically represents a better occupational opportunity. This is the second aspect of opportunity in the analysis.

In order to answer what skills increase the probability of being formally employed, a *probit regression model* was applied. Probability, or probit, models are used to model binary outcome variables where the probability that an observation falls into either one or the other category is estimated. The formality variable is of binary character and equals 1 if the respondent is a wage-worker with social security, and 0 otherwise.

Two probability models were also fitted to estimate the likelihood of being employed in occupations associated with certain skill levels. The dependent variables of interest were constructed using ILO's International Classification of Occupation (ISCO) (see table 5.3). The classifications were based on the nature of work and the qualifications required for competent performance of the job tasks (ILO, 2022). The first model estimated the probability of being employed either in a mid- or a high-skilled occupation compared to a low-skilled occupation. By grouping the two highest categories, the model answers what motivates acquiring *any* skill beyond the lowest level.

**Table 5.3:** International Standard Classification of Occupations (ISCO-08)[3]

| Broad Skill Level | Occupation |
|---|---|
| **Skill level 3 (high)** | 1. Managers |
| | 2. Professionals |
| | 3. Technicians and associate professionals |
| **Skill level 2 (medium)** | 4. Clerical support workers |
| | 5. Service and sales workers |
| | 6. Skilled agricultural, forestry and fishery workers |
| | 7. Craft and related trades workers |
| | 8. Plant and machine operators, and assemblers |
| **Skill level 1 (low)** | 9. Elementary occupations |

[3] The latest version, ISCO-08 is the fourth iteration following ISCO-58, -68 and -88.

The second model estimated what motivates the highest level of skill acquisition, i.e. beyond what low- and mid-skilled jobs require. Whereas an ordinal probit model using an ordinal skill-level variable would capture the effect for each skill category relative to the others, it assumes that an increase in one probability simultaneously decreases the other two. The advantage of this two-stage probit approach is that it captures the separate effects for two important transitions. The results from the probit models were analyzed by interpreting the marginal effects computed from the immediate regression output. The predictors and control variables were the same in all probit models as for the earnings regression model.

## 5.3 Limitations

Although the STEP measurement program holds a lot of data, it was available in cross-sectional format only. Whereas a snapshot of one point in time still provides a lot of useful information, the absence of a time dimension does not make it possible to follow labor market dynamics over time. Thus, no conclusions regarding the longevity of labor market mismatches can be drawn.

The data also poses an issue of representation. The final samples contain 2175 observations from the urban population in Ghana and 2479 observations from Kenya. Although the surveyed individuals were selected from a randomization process, the full urban population count for the year the survey was conducted measured 13.5 million in Ghana and 11 million in Kenya. Moreover, there is a difference in characteristics between urban and rural dwellers. Generally, urban populations tend to have better access to jobs and have higher educational levels (Zhang, 2006). Due to the relatively small sample size and the selection of urban residents only, findings will not be nationally representative.

Measuring skills is a challenge in itself. First, since skills requirements are ever-evolving and changing between and within occupations, there is yet no standard measure of skills (Allen & de Grip, 2012; ILO, 2018). Second, data comprising more dimensions of skills than education and literacy is scarce, especially for developing countries. Third, there is a tradeoff between advantages and disadvantages of each skills measurement method. The self-assessment method used in this thesis has the advantage of giving heterogeneous information across workers, with the obvious drawback being tendencies to overestimate skills requirements (Morsy & Mukasa, 2019). To get rid of estimation bias, a direct assessment in the form of standardized tests could be adopted. However, this method is both time consuming and complicated to use for any skill that is difficult to quantify, such as personality traits (Allen *et al.*, 2013).

Although the measurement methods in the STEP program are associated with some disadvantages, it remains the best available data option for the purpose of this research. The wide coverage of skills and individuals in the STEP program enables an extensive initial mapping of labor force potential in the two countries.

# 6 | Results

The results presented below are divided into descriptive and regression findings. Section 6.1 contains illustrations of educational and skills mismatches across different occupational skill levels (low, mid and high). The following section, 6.2, presents the regression output for earnings and labor market opportunity regressed on skills.

## 6.1 Descriptive Findings

The difference between each individual's ISCED level obtained and the ISCED level they believe is required for their job is summarized in averages per occupational category in figure 6.1. These findings represent the 53% of Ghanaian and 36% of Kenyan employed that were not perfectly matched in terms of educational level. Among these workers, it appears from the figure that mismatched Ghanaian workers were overeducated across all skill levels. The largest mismatch was found among those in low skilled occupations (0.84). On the contrary, mismatched workers in Kenya were generally undereducated and more so the higher the occupational skill level.

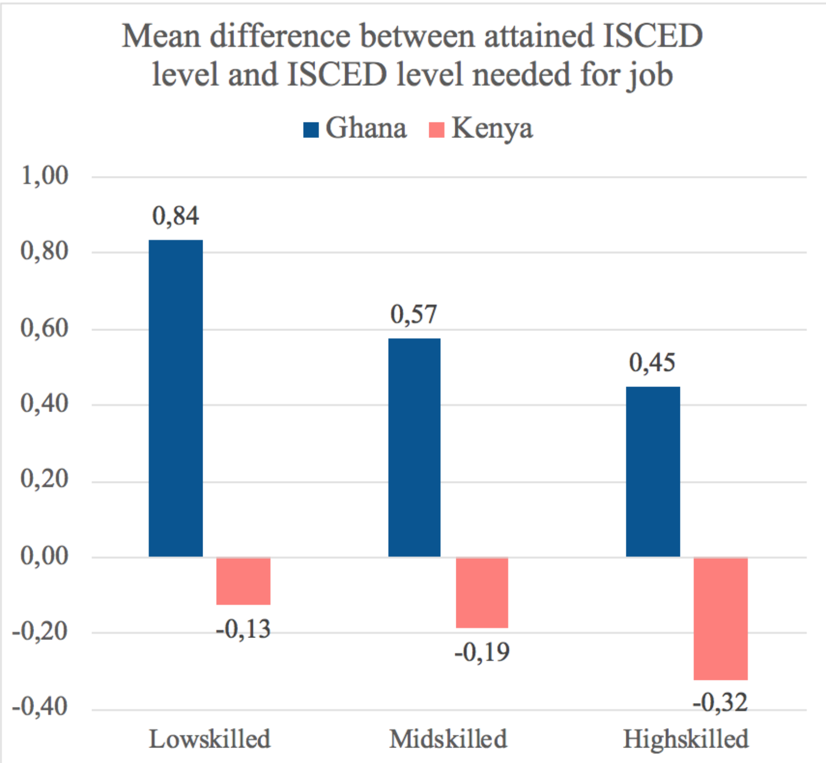



***Figure 6.1:*** *The average educational mismatch across occupational category for Ghana and Kenya measured by difference in obtained and required ISCED level*

With regards to skills, the degree of mismatch among the employed was generally higher in Kenya. Table 6.1 shows that the share of employed whose skills were not exactly matched between everyday life and work were higher in Kenya. It also shows that reading followed by writing accounted for larger mismatches than numeracy and computer use.

**Table 6.1:** The share of mismatched workers in total employment within each skill domain

| Skill | Share of mismatched workers per skill in total employment | |
|---|---|---|
| | Ghana | Kenya |
| Reading | *36.7%* | *42.3%* |
| Writing | *16.3%* | *25.5%* |
| Numeracy | *10.9%* | *12.6%* |
| Computer | *9.3%* | *15.4%* |

Whereas table 6.1 shows the size of the mismatched groups in the workforce, figure 6.2 demonstrates the degree of mismatch within these groups. Generally, people reported a *higher* use of reading, writing, numeracy and computer skills in their daily life compared to what they use at work. Thus, there was a presence of skills overutilization in both Ghana and Kenya.

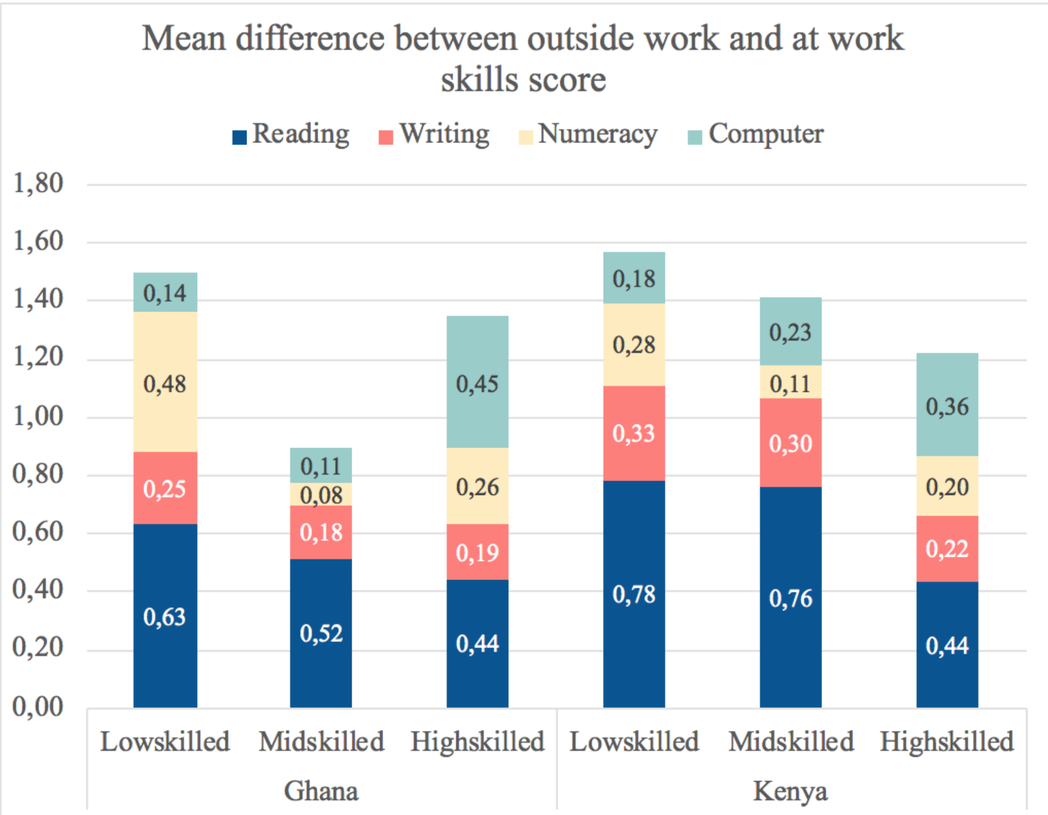



***Figure 6.2:** The average skill mismatch across occupational categories for mismatched workers in Ghana and Kenya*

Overall, mismatched workers in low-skilled occupations accounted for the largest unexploited potential in both countries, where particularly reading skills were not put to use in the workplace. In the mid-skilled occupations, all skill domain mismatches were smaller compared to the low-skilled category with a larger contrast in Ghana. A more effective use of numeracy skills was the main explanation for the reduction of total mismatches in mid-skilled occupations. While reading, writing and numeracy mismatches generally were smaller in high-skilled occupations, there was a substantial gap between those having computer skills and those using it at work.

## 6.2 Regression Analysis

The augmented Mincer earnings equation was run to test whether higher earnings were guaranteed from additional years of education, and/or the accumulation of other types of skills (see table 6.2). Columns 1-3 present the results from testing each skills category separately, while all variables were included in a complete model seen in column 4. In both Ghana and Kenya, workers could expect an earnings increase for each additional year of education. Although there was some fluctuation across models, the fourth and full model predicts the increase in log earnings to be 7.6% in Ghana and 3% in Kenya, all else equal. Formal employment was also predicted to reward workers in both countries. Compared to employees within the informal sector, formal workers had around 20% higher earnings.

In Ghana, neither cognitive skills nor personality traits affected log earnings. However, a higher ability to use a computer or carry out more complicated tasks (solving & learning) was translated into higher wages. For every unit the overall score of computer use increased, log earnings were expected to rise by 12%. Similarly, earnings rose with 9% for every unit increase in the solving & learning score.

In Kenya, job-specific skills in the form of computer use, autonomy and solving & learning were consistently significant predictors of earnings. Whereas all of them were positively related to log earnings, the largest effect was found for computer use where a one unit score increase would raise log earnings by around 30%. Writing, numeracy and openness were separately significant in models 1 and 2, but not in the full model. Age and conscientiousness were also inconsistently significant across the different regression specifications. The implications of these results will be further discussed in section 7.

**Table 6.2:** Stepwise OLS regression results, augmented Mincer equation

| | Ghana | | | | Kenya | | | |
|---|---|---|---|---|---|---|---|---|
| Dependent variable: | (1) Earnings | (2) Earnings | (3) Earnings | (4) Earnings | (1) Earnings | (2) Earnings | (3) Earnings | (4) Earnings |
| **Qualifications** | | | | | | | | |
| Education | 0.100$^{***}$ | 0.102$^{***}$ | 0.0792$^{***}$ | 0.0764$^{***}$ | 0.0608$^{***}$ | 0.0808$^{***}$ | 0.0351$^{***}$ | 0.0301$^{***}$ |
| | (0.0149) | (0.0134) | (0.0144) | (0.0160) | (0.00666) | (0.00605) | (0.00638) | (0.00671) |
| Tenure | 0.00164 | 0.00170 | 0.00144 | 0.00134 | -0.00000876 | -0.000165 | 0.000390 | 0.000278 |
| | (0.00110) | (0.00110) | (0.00110) | (0.00111) | (0.000893) | (0.000910) | (0.000850) | (0.000850) |
| Tenure squared | -0.00000167 | -0.00000185 | -0.00000129 | -0.00000112 | 0.00000521 | 0.00000560 | 0.00000392 | 0.00000429 |
| | (0.00000290) | (0.00000290) | (0.00000289) | (0.00000290) | (0.00000309) | (0.00000315) | (0.00000293) | (0.00000293) |
| **Cognitive skills** | | | | | | | | |
| Reading | -0.0389 | | | -0.0630 | 0.0493 | | | -0.000472 |
| | (0.0482) | | | (0.0484) | (0.0266) | | | (0.0256) |
| Writing | 0.102 | | | 0.0682 | 0.137$^{***}$ | | | 0.0527 |
| | (0.0594) | | | (0.0600) | (0.0342) | | | (0.0332) |
| Numeracy | 0.0626 | | | 0.0189 | 0.150$^{***}$ | | | 0.0378 |
| | (0.0576) | | | (0.0581) | (0.0395) | | | (0.0391) |
| **Personality** | | | | | | | | |
| Conscientiousness | | 0.0407 | | 0.0320 | | 0.0536 | | 0.0911$^{*}$ |
| | | (0.0744) | | (0.0739) | | (0.0497) | | (0.0464) |
| Openness | | 0.119 | | 0.115 | | 0.132$^{**}$ | | 0.0385 |
| | | (0.0702) | | (0.0698) | | (0.0459) | | (0.0432) |
| Emotional stability | | -0.00616 | | -0.000815 | | 0.0698 | | 0.0529 |
| | | (0.0671) | | (0.0667) | | (0.0489) | | (0.0455) |
| Agreeableness | | 0.0218 | | 0.00490 | | -0.0122 | | -0.0530 |
| | | (0.0636) | | (0.0634) | | (0.0449) | | (0.0419) |
| Extraversion | | -0.0243 | | -0.0367 | | 0.0486 | | 0.0416 |
| | | (0.0631) | | (0.0629) | | (0.0410) | | (0.0383) |
| **Jobspecific skills** | | | | | | | | |
| Interpersonal skills | | | 0.0213 | 0.0218 | | | -0.0207 | -0.0249 |
| | | | (0.0385) | (0.0390) | | | (0.0218) | (0.0219) |
| Computer use | | | 0.124$^{**}$ | 0.120$^{**}$ | | | 0.338$^{***}$ | 0.319$^{***}$ |
| | | | (0.0385) | (0.0392) | | | (0.0250) | (0.0263) |
| Autonomy | | | 0.0446 | 0.0459 | | | 0.131$^{***}$ | 0.124$^{***}$ |
| | | | (0.0495) | (0.0500) | | | (0.0335) | (0.0336) |
| Solving & learning | | | 0.0958$^{*}$ | 0.0911$^{*}$ | | | 0.0887$^{***}$ | 0.0751$^{**}$ |
| | | | (0.0379) | (0.0386) | | | (0.0239) | (0.0248) |
| **Controls** | | | | | | | | |
| Female | -0.206$^{**}$ | -0.194$^{*}$ | -0.137 | -0.127 | -0.0133 | -0.0359 | -0.0118 | 0.00135 |
| | (0.0761) | (0.0772) | (0.0775) | (0.0794) | (0.0481) | (0.0489) | (0.0457) | (0.0459) |
| Age | 0.00322 | 0.00303 | 0.00664 | 0.00714 | 0.00615$^{*}$ | 0.00576 | 0.00600$^{*}$ | 0.00613$^{*}$ |
| | (0.00446) | (0.00447) | (0.00452) | (0.00455) | (0.00289) | (0.00298) | (0.00275) | (0.00279) |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Formal | 0.236** | 0.247** | 0.194* | 0.189* | 0.421*** | 0.536*** | 0.242*** | 0.220*** |
| | (0.0908) | (0.0899) | (0.0949) | (0.0955) | (0.05868) | (0.05780) | (0.05960) | (0.05100) |
| $N$ | 953 | 953 | 953 | 953 | 1655 | 1655 | 1655 | 1655 |
| $R^2$ | 0.147 | 0.147 | 0.162 | 0.168 | 0.273 | 0.249 | 0.347 | 0.353 |
| adj. $R^2$ | 0.139 | 0.138 | 0.153 | 0.152 | 0.269 | 0.244 | 0.343 | 0.346 |

Standard errors in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

Whereas earnings is one aspect of potential opportunity from education and skills attainment, the type of employment is another. Table 6.3 presents the regression results from three probability models on employment opportunities. The first model (see first column for each country) estimates the marginal effect on the likelihood to be employed in a mid- or high-skilled occupation. The second model (second column per country) applies the same principle, but is exclusively concerned with the probabilities of high-skilled employment. The last column shows the regression output for the third probability model – the probability of being formally employed.

There were few skills investments beyond the requirements of low-skilled occupations that would increase the probability of escaping a low-skilled occupation in favor of a higher-skilled occupation. In Ghana, an additional year of schooling, better interpersonal skills and better solving & learning ability significantly increased the probability by less than 3% each. Correspondingly, schooling, conscientiousness and job-specific skills (interpersonal skills, computer use and solving & learning) were significant influencers in Kenya with a leverage of 5% and below. For the high-skilled occupations, cognitive skills gained importance and became positively significant together with education and computer skills. Being a formal worker also significantly increased the probability of working in the high-skill category.

**Table 6.3:** The marginal probability of being employed in a mid-to-high-skilled occupation; being employed in a high-skilled occupation; and working in the formal sector

| | Ghana | | | Kenya | | |
|---|---|---|---|---|---|---|
| Dependent variable: | Mid to high-skilled occup. | High-skilled occupation | Formal employment | Mid to high-skilled occup. | High-skilled occupation | Formal employment |
| **Qualifications** | | | | | | |
| Education | 0.00594$^{*}$ | 0.0336$^{***}$ | 0.0320$^{***}$ | 0.00270 | 0.0129$^{***}$ | 0.0157$^{***}$ |
| | (0.00237) | (0.00420) | (0.00488) | (0.00176) | (4.58) | (0.00299) |
| Tenure | 0.000194 | -0.000178 | 0.000193 | 0.000133 | -0.000458 | 0.000817$^{*}$ |
| | (0.000268) | (0.000308) | (0.000363) | (0.000249) | (-1.70) | (0.000338) |
| Tenure squared | 0.000000390 | 0.00000106 | 0.000000387 | -0.000000144 | 0.00000175$^{*}$ | -0.00000156 |
| | (0.00000124) | (0.000000761) | (0.000000925) | (0.000000907) | (2.04) | (0.00000119) |
| **Cognitive skills** | | | | | | |
| Reading | -0.00318 | 0.00697 | 0.00161 | -0.00671 | 0.0183$^{*}$ | 0.0222$^{*}$ |
| | (0.00726) | (0.0127) | (0.0153) | (0.00695) | (2.00) | (0.0102) |
| Writing | 0.0108 | 0.0506$^{***}$ | 0.0514$^{**}$ | 0.0269$^{*}$ | 0.0234$^{*}$ | 0.0262$^{*}$ |
| | (0.0109) | (0.0153) | (0.0184) | (0.0110) | (2.40) | (0.0120) |
| Numeracy | 0.00626 | 0.0518$^{**}$ | -0.0223 | 0.0238 | 0.0412$^{***}$ | 0.0151 |
| | (0.00888) | (0.0160) | (0.0184) | (0.0137) | (3.72) | (0.0140) |
| **Personality traits** | | | | | | |
| Conscientiousness | 0.00410 | -0.0108 | 0.0246 | 0.0335$^{**}$ | -0.0154 | 0.0139 |
| | (0.0108) | (0.0211) | (0.0247) | (0.0129) | (-0.99) | (0.0183) |
| Openness | 0.00607 | -0.00629 | -0.00575 | 0.00923 | 0.00319 | 0.00968 |
| | (0.00994) | (0.0192) | (0.0231) | (0.0122) | (0.21) | (0.0172) |
| Stability | -0.000382 | 0.0160 | 0.0180 | 0.0196 | -0.00610 | 0.0148 |
| | (0.00997) | (0.0191) | (0.0227) | (0.0133) | (-0.41) | (0.0177) |
| Agreeableness | -0.00905 | 0.0122 | -0.0196 | -0.0136 | 0.0383$^{**}$ | -0.00965 |
| | (0.00937) | (0.0175) | (0.0209) | (0.0127) | (2.77) | (0.0164) |
| Extraversion | -0.00770 | -0.00220 | -0.00453 | 0.00210 | 0.0126 | 0.0119 |
| | (0.00945) | (0.0173) | (0.0209) | (0.0111) | (0.97) | (0.0147) |
| **Jobspecific skills** | | | | | | |
| Interpersonal skills | 0.0158$^{**}$ | 0.0398$^{***}$ | -0.0222 | 0.0551$^{***}$ | 0.0141 | -0.0287$^{***}$ |
| | (0.00576) | (0.0105) | (0.0126) | (0.00567) | (1.84) | (0.00838) |
| Computer use | 0.0113 | 0.0270$^{**}$ | 0.0481$^{***}$ | 0.0316$^{**}$ | 0.0450$^{***}$ | 0.0890$^{***}$ |
| | (0.00708) | (0.00899) | (0.0111) | (0.0101) | (6.29) | (0.00814) |
| Autonomy | 0.00538 | -0.0194 | -0.129$^{***}$ | 0.0125 | 0.0138 | -0.0934$^{***}$ |
| | (0.00739) | (0.0137) | (0.0153) | (0.00973) | (1.24) | (0.0128) |
| Solving & learning | 0.0222$^{***}$ | 0.0200 | 0.0270$^{*}$ | 0.0298$^{***}$ | 0.0387$^{***}$ | -0.00171 |
| | (0.00627) | (0.0105) | (0.0126) | (0.00714) | (4.53) | (0.00984) |
| **Controls** | | | | | | |
| Female | 0.0532$^{***}$ | -0.0432 | -0.0628$^{*}$ | -0.0226 | -0.0200 | -0.0289 |
| | (0.0145) | (0.0222) | (0.0263) | (0.0134) | (-1.32) | (0.0179) |
| Age | 0.000891 | 0.000383 | 0.000629 | 0.000586 | 0.000583 | 0.00103 |
| | (0.000709) | (0.00130) | (0.00151) | (0.000779) | (0.60) | (0.00111) |
| Formal | -0.0352$^{**}$ | 0.116$^{***}$ | | 0.00183 | 0.0631$^{***}$ | |
| | (0.0134) | (0.0220) | | (0.0196) | (3.76) | |
| *N* | 1023 | 1023 | 1023 | 1776 | 1776 | 1776 |

Standard errors in parentheses
$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.00$

Across Ghana and Kenya there were generally small differences with regards to the predictors of formal employment. In both countries, educational attainment positively and significantly affected the likelihood of being formally employed with a slightly higher leverage in Ghana (3.2%) than Kenya (1.6%). Neither experience at current occupation nor any of the Big Five personality traits had significant or large effects on the probability of being a formal worker in either country.

Within the cognitive skills category, a one unit increase in writing score increased the likelihood of being formally employed by 5.1% in Ghana, while both writing and reading increased the likelihood in Kenya by 2.6% and 2.2% respectively. Among all skill categories combined, job-specific skills were most significant in affecting formal employment probabilities. The use of technology positively influenced the likelihood of formal employment across both Ghana and Kenya with 4.8% and 8.9% respectively, whilst a higher use of task and organizational freedom at work (autonomy) decreased that same probability with 12.9% and 9.3% in each country.

The results show a few country-specific results. Interpersonal skills were a significant predictor only in Kenya (-2.9%) while solving & learning only affected the likelihood for Ghanaian individuals (2.7%). Furthermore, a gender difference was detected in Ghana where women suffered a 6.3% lower chance of being a formal worker compared to men, all else equal.

# 7 | Discussion

For an economy to make best use of the potential within its workforce, mismatch analysis offers a helpful tool to map out whether and where workers are inefficiently allocated over available jobs. Since more than a third of Kenya's and over half of Ghana's employed workers were engaged in a job where the obtained and required level of education did not match, a substantial amount of educational investments did not result in the expected outcome. Across all occupations, there was a consistent trend of overeducation in Ghana and undereducation in Kenya. However, it remains ambiguous from the results whether it is the educational level or the educational requirement that is driving the mismatches.

The type of mismatch measurement used in this thesis is a relative measure of two components; educational level and educational requirement, where the latter is assessed by the respondent. Mismatches arise if one component is either higher or lower relative to the other. Regardless of the main driver, the justification of investing both time and money for an educational degree is likely underpinned by an expectation of putting the degree to effective use. Yet, a lot of Ghanaian workers ended up in a job with less educational requirements. While education might have helped workers find employment, it did not help them as much as predicted by human capital theory to find a job matching their educational level.

Firstly, these results point to the need of improving job search efficiency. In order to enable appropriate educational investments, individuals need to relate their investment decisions to current labor market realities. Providing early knowledge of entry requirements and potential educational returns could help individuals make more informed decisions regarding their educational attainment. Secondly, these results suggest that the current allocation of workers across jobs is suboptimal from an input-output perspective. Suppose overeducated workers were reallocated to other, more demanding jobs, or if educational skills were better integrated in current workplaces. Then, the time spent learning skills and obtaining an educational degree would be put to more efficient use and relative labor productivity would increase using already existing skills.

In the case of Kenya, there were higher educational demands than there was supply. In order for the workforce to meet the demands of the economy, educational levels need to be raised in relation to requirements. However, with regards to skills beyond educational attainment, all workers practiced their cognitive and computer skills on a level below their overall capacity. The fact that mismatched Kenyan workers generally had excess capacity in terms of skills but inferior educational degrees offers three insights;

First, that all workers were capable of performing their cognitive and computer related work tasks *despite* some being undereducated. Second, that educational attainment and skills attainment need not to be used interchangeably as previously noted by for example Allen & De Weert (2007) and Allen & Van der Velden (2001), and third, that results might have been subject to estimation bias. As the educational requirements were reported by the workers themselves, there were several factors that could have influenced the likelihood of over- or underestimating job requirements. For example, cultures of thought about one's own abilities and/or qualification inflation, where the respondent believes that a certain level of skill must be associated with a higher level of education than it actually is. In the absence of confirmed bias or no bias, the results should be interpreted with consideration to this human factor.

In both countries, a logical pattern of mismatches across different skill-leveled occupations was found. The most unrealized cognitive skill potential was present in the low-skilled occupations. These occupations traditionally include more body work and less clerical tasks. The cause of the small mismatch in computer skills in low-skilled occupations is likely due to both a low at- and outside-work computer use score. For the high-skilled occupations, computer mismatches were much larger. This is likely due to higher requirements and particularly higher skills among these workers.

Generally, more Kenyans than Ghanaians experienced a cognitive or computer skills mismatch, and the degree of that mismatch was on average higher in Kenya. Since over half of Kenya's urban workforce was employed in agriculture, a lot of this unused skill potential is probably locked within the primary sector. Releasing labor from agriculture would increase the inflow of workers to mid- and high-skilled occupations and thereby reduce the underutilization of skills. Such a transition could for example be facilitated by initiatives to make agriculture less labor intensive.

The results indicate that both the Kenyan and the Ghanaian workforce were in disequilibrium in terms of the supply and demand of skills. Although this thesis did not document changes over time, it can conclude that mismatches were present at least at this one point in time, thereby constituting a significant time- and resource-demanding imbalance to restore. According to human capital theory, this supply-demand imbalance will not persist over time as supply will alter to match demand. Assignment theory, on the other hand, recognizes a possible persistence of these mismatches over time as they are products of more dynamic supply and demand changes. As the smallest degree of mismatch was found in high-skilled occupations, the overall matching pattern corresponded to that of assignment theory.

Of the wide scope of skill domains included in the concept of human capital, this thesis disentangles which were rewarded on the labor market using OLS and probit regressions More years of schooling, computer skills and solving & learning abilities were positively correlated with earnings across all model specifications in both countries. Particularly high returns could be expected from an increase in computer use score that predicted an earnings increase by 12% in Ghana and about 30% in Kenya. These results were consistent and robust also when the same regression was run on an unspecified sample (see appendix, table A).

The slight variation between the significance and coefficients of the cognitive skills variables across model specifications was likely due to the higher correlation between these variables compared to the rest. Although the overall degree of multicollinearity was not alarmingly high, it was the highest within the cognitive skills category and between cognitive skills and education, especially for Kenya (see appendix, tables B and C). Thus, some stability of the cognitive skills estimates were probably lost due to the presence of multicollinearity.

Although some of the effects from the cognitive skills might have been picked up by the education variable due to multicollinearity, educational attainment rather than concrete skills attainment were more important for earnings. Although there is an established positive relationship between cognitive skills and earnings in the literature, years of education was the better predictor of earnings in Ghana and Kenya. Signaling theory proposes that the recruitment of skills is done using educational qualification as a proxy for skills rather than direct assessments of skills. Accordingly, the employment and thereby the earnings of the individual would be better explained by the individual's obtained level of education than the actual skills obtained at that particular level.

Apart from earnings, better employment opportunities were represented by formal employment or employment in a higher-skilled occupation. Education and several job-specific skills increased the probability of being a formal worker in both countries. In addition to improved working conditions, being a formal worker also had robust and positive effects on earnings seen from the earnings regression. Generally, few skills significantly increased the probability to escape a low-skilled occupation in favor of a higher-skilled occupation. The likelihood of being employed in a higher-skilled occupation was best predicted by skills that were related to specific job tasks such as interactive ability and being able to solve more complicated or time consuming problems, rather than more general, cognitive skills.

No significant wage or opportunity returns were found for the Big Five personality traits. Although Mohammed et al. (2021) confirmed some positive relationships between personality and wages in Ghana, they defined their samples differently and focused on gender and type of employment differences. In general, the literature on personality traits returns are mixed, calling for more research and refined data and methods.

Before concluding, two further considerations need to be highlighted. First, the skills mismatch analysis conducted in this thesis did not deal with the unexploited potential represented by the unemployed population. The share of unemployed and inactive individuals was 14.7% in Ghana and 25.5% in Kenya. Taking this aspect into account, Kenya had a larger share of its population that were not at all taking part in value adding activities in the economy compared to Ghana. Second, the large reduction in the number of observations from adding personality variables in the earnings regression for Ghana (see appendix, table A) suggests that non-responses or missing data was a much more present problem in the sample of Ghana than Kenya. This near halving of the sample size decreases representativity of the population as well as the predictive power of the model.

# 8 | Conclusion

Young people are faced with several challenges entering the labor market, especially in developing countries. One of them is finding a job that preferably one that matches their level of skills and education. This thesis argues that over- and underutilization of skills represent unused potential and that skills are associated with different economic and opportunity returns. By exploring the wide variety of existing skills within the urban workforces of Ghana and Kenya, the study contributes to a better understanding of the skills that are currently unexploited on the labor market and which skills that are more profitable to invest in.

The thesis found that Ghana had a higher employment rate than Kenya, but a larger number of mismatched workers in terms of education. Generally, the Ghanaian workers had a higher level of education and a higher level of cognitive and computer skills than what was required to perform their job satisfactorily. In Kenya, workers also possessed surplus cognitive and computer skills, but compared to Ghana they were more frequent. Even though everyone met the skills requirement with margins, the average Kenyan worker was undereducated for their job.

Whereas Kenya had larger unexploited potential represented by the unemployed, they did not face a substantial problem of underutilization of educational investments compared to Ghana. Furthermore, the skills mismatch results suggested that both countries had unexploited productivity gains represented by a disadvantageous allocation of cognitive and computer skills across jobs. However, since the mismatch variables were partly determined by the worker's own estimation of educational and skills requirements, the size of the mismatch was likely biased to some degree. Before suggesting potential policy solutions, the extent of mismatches should be confirmed using a standardized measurement of skills and educational requirements.

The skills that generated the best earnings and occupational opportunities were in broad terms the same across Ghana and Kenya. More years of schooling, computer skills and solving & learning abilities positively predicted both earnings and the likelihood to be employed in a higher skilled occupation or work within the formal sector. Cognitive skills had small or no impact, suggesting that educational qualification could have had a signaling function for cognitive skills. Personality traits such as extraversion or stability were generally not rewarded on the labor market, while abilities related to specific job tasks were. For example, computer skills predicted an earnings increase by 12% in Ghana and 32% in Kenya.

Lastly, the formality of employment stood for several positive effects. Employees in the formal sector could expect social security and higher predictability of employment as well as significantly higher earnings. The probability of being employed in a higher-skilled occupation also increased by 11.6% in Ghana and 6.3% in Kenya for formal employees.

In terms of workforce potential, Ghana and Kenya are similar in many ways. Both countries have young and growing workforces offering productive potential in terms of manpower and abilities and overqualified workers in all occupations. The main differences lie in their economic structure and ability to provide employment opportunities. Going forward, Ghana and Kenya need to efficiently harness this potential with consideration to their respective preconditions in order to optimize productivity and sustain economic growth.

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# Appendix

**Table A:** Augmented Mincer Equation – Unspecified sample

| | Ghana | | | | Kenya | | | |
|---|---|---|---|---|---|---|---|---|
| Dependent variable: | Earnings | Earnings | Earnings | Earnings | Earnings | Earnings | Earnings | Earnings |
| **Qualifications** | | | | | | | | |
| Education | 0.0411*** | 0.100*** | 0.0367*** | 0.0764*** | 0.0610*** | 0.0826*** | 0.0357*** | 0.0301*** |
| | (0.00913) | (0.0135) | (0.00777) | (0.0160) | (0.00656) | (0.00603) | (0.00631) | (0.00671) |
| Tenure | 0.00237** | 0.00199 | 0.00230** | 0.00134 | 0.0000432 | -0.000113 | 0.000345 | 0.000278 |
| | (0.000832) | (0.00111) | (0.000841) | (0.00111) | (0.000888) | (0.000907) | (0.000847) | (0.000850) |
| Tenure squared | -0.00000374 | -0.00000251 | -0.00000392 | -0.00000112 | 0.00000465 | 0.00000507 | 0.00000412 | 0.00000429 |
| | (0.00000223) | (0.00000293) | (0.00000224) | (0.00000290) | (0.00000304) | (0.00000310) | (0.00000293) | (0.00000293) |
| **Cognitive skills** | | | | | | | | |
| Reading | -0.0208 | | | -0.0630 | 0.0543* | | | -0.000472 |
| | (0.0424) | | | (0.0484) | (0.0263) | | | (0.0256) |
| Writing | 0.118* | | | 0.0682 | 0.141*** | | | 0.0527 |
| | (0.0530) | | | (0.0600) | (0.0342) | | | (0.0332) |
| Numeracy | 0.131** | | | 0.0189 | 0.144*** | | | 0.0378 |
| | (0.0462) | | | (0.0581) | (0.0394) | | | (0.0391) |
| **Personality** | | | | | | | | |
| Conscientiousness | | 0.0591 | | 0.0320 | | 0.0545 | | 0.0911* |
| | | (0.0749) | | (0.0739) | | (0.0494) | | (0.0464) |
| Openness | | 0.114 | | 0.115 | | 0.135** | | 0.0385 |
| | | (0.0709) | | (0.0698) | | (0.0457) | | (0.0432) |
| Stability | | -0.0268 | | -0.000815 | | 0.0495 | | 0.0529 |
| | | (0.0675) | | (0.0667) | | (0.0485) | | (0.0455) |
| Agreeableness | | 0.0179 | | 0.00490 | | -0.0100 | | -0.0530 |
| | | (0.0642) | | (0.0634) | | (0.0447) | | (0.0419) |
| Extraversion | | -0.00429 | | -0.0367 | | 0.0254 | | 0.0416 |
| | | (0.0633) | | (0.0629) | | (0.0409) | | (0.0383) |
| **Job specific skills** | | | | | | | | |
| Interpersonal skills | | | 0.0502 | 0.0218 | | | -0.0183 | -0.0249 |
| | | | (0.0313) | (0.0390) | | | (0.0217) | (0.0219) |
| Computer use | | | 0.163*** | 0.120** | | | 0.334*** | 0.319*** |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | (0.0360) | (0.0392) | | | (0.0248) | (0.0263) |
| Autonomy | | | 0.0500 | 0.0459 | | | 0.126*** | 0.124*** |
| | | | (0.0388) | (0.0500) | | | (0.0333) | (0.0336) |
| Solving & learning | | | 0.0696* | 0.0911* | | | 0.0883*** | 0.0751** |
| | | | (0.0306) | (0.0386) | | | (0.0238) | (0.0248) |
| **Control variables** | | | | | | | | |
| Female | -0.294*** | -0.221** | -0.250*** | -0.127 | -0.00899 | -0.0286 | -0.0100 | 0.00135 |
| | (0.0608) | (0.0777) | (0.0621) | (0.0794) | (0.0478) | (0.0488) | (0.0455) | (0.0459) |
| Age | -0.00312 | 0.00292 | -0.000323 | 0.00714 | 0.00615* | 0.00561 | 0.00598* | 0.00613* |
| | (0.00336) | (0.00451) | (0.00344) | (0.00455) | (0.00289) | (0.00298) | (0.00274) | (0.00279) |
| Formal | 0.339*** | 0.255** | 0.245** | 0.189* | 0.415*** | 0.527*** | 0.245*** | 0.220*** |
| | (0.0853) | (0.0909) | (0.0903) | (0.0955) | (0.0584) | (0.0578) | (0.0594) | (0.0600) |
| *N* | 1707 | 964 | 1676 | 953 | 1700 | 1693 | 1667 | 1655 |
| $R^2$ | 0.128 | 0.147 | 0.139 | 0.168 | 0.270 | 0.243 | 0.346 | 0.353 |
| adj. $R^2$ | 0.123 | 0.137 | 0.134 | 0.152 | 0.267 | 0.238 | 0.342 | 0.346 |

**Table B:** Matrix of correlations, Ghana

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Earnings (ln) | 1.000 | | | | | | | | | | | | | |
| (2) Education | 0.337 | 1.000 | | | | | | | | | | | | |
| (3) Reading | 0.180 | 0.507 | 1.000 | | | | | | | | | | | |
| (4) Writing | 0.220 | 0.475 | 0.511 | 1.000 | | | | | | | | | | |
| (5) Numeracy | 0.131 | 0.292 | 0.149 | 0.177 | 1.000 | | | | | | | | | |
| (6) Conscientiousness | 0.133 | 0.226 | 0.159 | 0.128 | 0.089 | 1.000 | | | | | | | | |
| (7) Openness | 0.149 | 0.240 | 0.188 | 0.160 | 0.105 | 0.315 | 1.000 | | | | | | | |
| (8) Stability | 0.066 | 0.108 | 0.099 | 0.073 | 0.063 | 0.121 | 0.039 | 1.000 | | | | | | |
| (9) Agreeableness | 0.123 | 0.238 | 0.169 | 0.131 | 0.087 | 0.301 | 0.352 | 0.063 | 1.000 | | | | | |
| (10) Extraversion | 0.057 | 0.186 | 0.122 | 0.110 | 0.026 | 0.058 | 0.099 | -0.044 | 0.143 | 1.000 | | | | |
| (11) Interpersonal skills | 0.088 | 0.185 | 0.182 | 0.173 | 0.102 | 0.018 | 0.076 | 0.003 | 0.022 | 0.086 | 1.000 | | | |
| (12) Computer use | 0.287 | 0.548 | 0.392 | 0.389 | 0.256 | 0.196 | 0.203 | 0.064 | 0.174 | 0.157 | 0.109 | 1.000 | | |
| (13) Autonomy | -0.053 | -0.158 | -0.146 | -0.196 | 0.009 | -0.057 | -0.068 | -0.025 | -0.031 | -0.093 | 0.069 | -0.183 | 1.000 | |
| (14) Solving & learning | 0.212 | 0.300 | 0.238 | 0.288 | 0.211 | 0.112 | 0.110 | 0.034 | 0.146 | 0.096 | 0.225 | 0.312 | -0.060 | 1.000 |

**Table C:** Matrix of correlations, Kenya

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Earnings (ln) | 1.000 | | | | | | | | | | | | | |
| (2) Education | 0.402 | 1.000 | | | | | | | | | | | | |
| (3) Reading | 0.315 | 0.513 | 1.000 | | | | | | | | | | | |
| (4) Writing | 0.355 | 0.448 | 0.571 | 1.000 | | | | | | | | | | |
| (5) Numeracy | 0.320 | 0.394 | 0.451 | 0.545 | 1.000 | | | | | | | | | |
| (6) Conscientiousness | 0.095 | 0.073 | 0.072 | 0.060 | 0.025 | 1.000 | | | | | | | | |
| (7) Openness | 0.174 | 0.221 | 0.212 | 0.190 | 0.219 | 0.197 | 1.000 | | | | | | | |
| (8) Stability | 0.064 | 0.053 | 0.047 | 0.077 | 0.057 | 0.147 | 0.083 | 1.000 | | | | | | |
| (9) Agreeableness | 0.049 | 0.049 | 0.061 | 0.076 | 0.080 | 0.187 | 0.217 | 0.046 | 1.000 | | | | | |
| (10) Extraversion | 0.084 | 0.122 | 0.096 | 0.085 | 0.037 | 0.169 | 0.196 | 0.029 | 0.110 | 1.000 | | | | |
| (11) Interpersonal skills | 0.084 | 0.147 | 0.181 | 0.139 | 0.136 | 0.028 | 0.082 | -0.015 | 0.039 | 0.073 | 1.000 | | | |
| (12) Computer use | 0.513 | 0.589 | 0.504 | 0.547 | 0.480 | 0.043 | 0.242 | 0.052 | 0.075 | 0.103 | 0.129 | 1.000 | | |
| (13) Autonomy | 0.101 | 0.037 | 0.061 | 0.025 | 0.092 | 0.034 | 0.056 | 0.018 | 0.044 | 0.004 | 0.246 | 0.024 | 1.000 | |
| (14) Solving & learning | 0.291 | 0.291 | 0.320 | 0.379 | 0.400 | -0.014 | 0.158 | 0.016 | 0.061 | 0.052 | 0.165 | 0.380 | 0.083 | 1.000 |