FIELDS OF STUDY AND GRADUATES' LABOUR MARKET OUTCOMES IN SOUTH AFRICA.

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Abstract

This study investigates job-education mismatch in South Africa based on graduates' fields of study. Using data from the Quarterly Labour Force Survey for the period 2015 to 2019, we explore graduate endpoints in the labour market by determining how well-matched they are to their occupation and the association between being horizontally or vertically mismatched on earnings as well as job tenure. The results of the study found that Education and Health graduates are better matched to their occupations than Commerce and STEM graduates. Using a multinomial logistic regression to evaluate the likelihood of working in a match occupation, the study found that Commerce graduates are the most likely to transition into an occupation that they are overeducated for, while STEM graduates are more likely to transition into a horizontally mismatched occupation when compared to the other fields of study observed. Furthermore, using Mincerian OLS regressions, the study found a significant negative association between earnings and being overeducated among STEM and Commerce graduates. Lastly, this study also found a significant negative association between being horizontally mismatched and tenure among STEM and Commerce youth graduates.

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INTRODUCTION

Every year, thousands of potential graduates enrol in universities and colleges across the country aiming to obtain their qualifications to better their chances of entering the labour market. Unfortunately, not all graduates are successfully absorbed into the labour market. The South African economy has not been successful in generating sufficient employment growth, and thus, graduates are naturally affected. The most recent data from Statistics South Africa (2022) shows that the labour market absorption rate in South Africa (SA) is low (42.4%) and those with less education make the situation a problem as only a small proportion of workers have tertiary qualifications. Furthermore, the labour market suffers from a high skills shortage and youth unemployment. With a youth unemployment rate greater than the national average, youths in SA continue to bear the burden of unemployment regardless of their educational attainment. In the first quarter of 2022, the narrow youth unemployment rate for those between the ages of 15-24 was 63.9%[1] and for those between 25-34 years old was 42.1% and the national unemployment rate was 34.5%[2] (Stats SA, 2022). Moreover, when comparing the unemployment rate of young graduates on a year-on-year basis, in the first quarter of 2022, the unemployment rate of young graduates aged 15–24 years decreased from 40.3% (Q1:2022) to 32.6%, and it increased by 6.9 percentage points to 22.4% for those aged 25–34 years (Stats SA, 2022). Therefore, there is still a significant number of unemployed graduates.

The structure of employment has moved from manual labour in the manufacturing sector to occupations in the service sector globally and this shift has increased the need for higher levels of knowledge and skills (Breier, 2010). Furthermore, the demand for graduate knowledge and skills in various occupations has been driven by technological advancement and global economic forces (Breier, 2010). In South Africa, however, the economy could be performing well and yet, there would still be a higher unemployment rate recorded which means that unemployment in SA could be affected mainly by structural factors than economic factors (Nonyana & Njuho, 2018). Skills mismatch and technological advancement are the main structural factors that contribute to the unemployment conditions in SA (Nonyana & Njuho,

[1] As of the fourth quarter of 2022 youth unemployment rate, measuring job-seekers between 15 and 24 years old is 61% (Stats SA, 2022).
[2] The unemployment rate is currently 32.7% (Stats SA, 2022)

2018). The increase in enrolments in higher education has also been found to be disproportionate to the increase in economic growth in Africa (Nonyana & Njuho, 2018).

One of the main contributing factors to graduate unemployment is the mismatch between graduates’ qualification types and the skills required in the labour market (Breier, 2010). Those who are employed may be perfectly matched to their occupation or mismatched. A mismatch occurs when graduates that are employed are either over-qualified or under-qualified (Vertical skills mismatch) for their occupation or their occupation does not significantly relate to their field of study (Horizontal mismatch). Horizontal mismatch manifests when employees' occupations are not aligned with the knowledge and skills they acquired in formal/higher education. Therefore, this study seeks to evaluate graduate endpoints in the labour market based on their field of study. Some fields of study provide students with more productive and challenging skills and knowledge that are related to specific jobs than other education fields that only provide general skills. Therefore, job applicants that are well-matched to the skill requirements of a job are more productive and need less training, and are also more likely to earn higher labour market returns than those that only obtained general skills (Klein, 2016). Occupational mismatch occurs when there is a disparity between workers’ knowledge and skills with those required by their job (Flisil et al., 2016). To combat unemployment and strengthen competition in an economy, it is vital to match workers’ potential with their actual jobs (Flisil et al., 2016). Better job matching improves the welfare of an individual and positively impacts the productivity and growth of an economy (Flisil et al., 2016).

There is a lack of sufficient studies that provide adequate research and empirical findings relating to the job-education mismatch of South African graduates. This study aims to contribute to existing works of literature on graduates' labour market outcomes in South Africa by investigating job-education mismatch both horizontally and vertically conditioned on graduates' fields of study. In addition, this study evaluates the association between being mismatched and earnings as well as job tenure among graduates from different fields of study. We use data from the Quarterly Labour Force Survey (QLFS) which is representative of the South African population from the period 2015-2019 for our analyses. We pool the data in order to increase the number of observations for graduates. We use pre-Covid data because of the decline in response rate in the QLFS during the lockdown period. The pandemic altered the labour market dynamics in South Africa. Over 2 million people lost their jobs and there was an increase in internal migration which changed the composition of households (Bhorat, Köhler

& Stanwix, 2022). Furthermore, the use of pre-Covid data allows us to evaluate the dynamics of graduates' occupational mismatch before the pandemic.

This study will provide insight into job-education mismatch among graduates in South Africa and the labour market implications of being mismatched. This study will also provide evidence of the importance of matching graduates' fields of study to their occupations in order to maximize their potential in the labour market.

Research Question

This study seeks to investigate job-education mismatch based on fields of study. To do so, the following research questions will be addressed in this study:

1. What is the job-education mismatch for different fields of study?
2. What is the likelihood for graduates to be employed in their related field of occupation?
3. What is the association between job-education mismatch and earnings conditioned on the field of study?
4. What is the association between occupational mismatch and job tenure conditioned on the field of study?

LITERATURE REVIEW

Various studies have investigated the labour market outcomes of graduates (Mason et al., 2009; McGuinness 2003; Tomlinson, 2008). These studies have shown that graduates' labour market outcomes are dependent on the structure of a country's labour market (competitive or non-competitive graduate labour market) and the academic qualification (field of study, course design and delivery). In South Africa, there has been an increase in the number of graduates, however, the type of qualifications that graduates hold has been concerning as specific groups of graduates still have difficulties in finding employment (Graham et al., 2019).

Graduates from various fields of study obtain different skills and competencies through their studies. Fields of study may be different in the complexity of the curriculum, learning environments and the provision of general academic skills (Klein, 2016). Therefore, certain fields of study may provide students with more job-related skills and train students for specific occupations, while others provide more general skills and lack a specific occupational orientation. Moreover, the benefits of human capital acquired during studies are dependent on the demand for specific skills (Klein, 2016).

Moleke (2010) explained that one of the reasons for the low labour market absorption rate of graduates in SA is the mismatch between the skills and qualification types demanded in the labour market and the outputs of the higher education system. This is evident in the high rate of unemployment for graduates from the field of Humanities, Art and Social Sciences in SA compared to graduates in Science and Engineering field (Moleke, 2010). Various studies have also found that graduates in Humanities, Social Sciences and Arts experience higher levels of unemployment than graduates in Science, technology, engineering and mathematics (Van Broekhuizen, 2016; Klein, 2016). Mncayi and Dunga (2016) investigated the relationship between career choice and the length of unemployment among graduates from the University of North West in South Africa using ordinary least squares (OLS) regression, an analysis of variance model and various descriptive analyses. Data was collected through a survey questionnaire given to alumni graduates from the university's alumni database and the empirical result found that certain majors held by graduates influence both their employment status and their duration of finding employment. Graduates that majored in politics, public management, public administration, labour relations management, industrial psychology and human resources had the longest waiting time before securing a job although they remain the most popular majors. However, the sample data used by Mncayi and Dunga (2016) for their analyses were not representative of the entire population of SA. This study uses data from a representative labour market survey, QLFS that is publicly available and representative of the South African population to investigate graduates' labour market outcomes based on their study fields by evaluating occupational mismatch both horizontally and vertically.

The conceptualizing and measuring of occupational mismatch are vital as different methods evaluate different aspects of occupational mismatch. A popular method of measuring occupational mismatch is by identifying workers as 'overeducated' (Vertical mismatch) if their educational credentials are greater than those required for a particular occupation (Grapsa, 2017). Skills mismatch defined as the underutilisation of acquired skills or the lack of adequate skills to perform a job may also be used to measure occupational mismatch (Grapsa, 2017). Flisil et al. (2016) argued that skill and education mismatch do not measure the same phenomenon. Using data from 17 European countries and the Program for the International

Assessment of Adult Competencies (PIAAC)[3] survey to determine individual occupational mismatch on both over-education and over-skilling using both subjective and objective measures, Flisil et al. (2016) found that the percentage of individuals that were mismatched in terms of both skill and education were significantly small. Skills mismatch and occupational switching may be caused by workers' imperfect knowledge about their true abilities at the time of joining the labour market and also when young employees misjudge their learning capabilities and work in occupations where the skill requirements do not align with their set of skills (Flisil et al., 2016).

Occupational mismatch affects both individuals and the economy as a whole. Sahin et al. (2012) investigated the contribution of occupational mismatch to the rise in unemployment in the United States. Using vacancy data from the JOLTS (Job Openings and Labour Survey) and HWOL (Help Wanted OnLine) and an index for mismatch which measured the fraction of hires lost due to misallocation, they found that mismatch across occupations and industries accounts for a third of the total recorded increase in the unemployment rate. Moore and Rosenbloom (2016) used two hundred and twenty-one Israeli participants to examine vertical mismatch (over-education) and horizontal match (match of employees' occupation field and education field) in Israel. They found that horizontal mismatch reduces the earnings level of workers, especially for those who experience horizontal mismatch throughout their careers. Furthermore, the probability of furthering higher education is lower for individuals that are horizontally mismatched than those that are horizontally matched (Moore & Rosenbloom, 2016). However, Schweri, Eymann & Aepli (2020) study on horizontal mismatch and vocational education using data from the Swiss Household Panel in the period 1999 to 2016 with subjective and objective measures of mismatch found that the wage penalties for being horizontally mismatched due to vocational education are small. They found that not working in a learned occupation does not result in a large wage effect. The wage penalty was 3.6% ($P<0.01$) for those that self-reported as being horizontally mismatched.

In a study on the income penalty of education-occupation mismatches among men and women aged 28-39 with higher education living in Sweden in 2003, Nordin, Persson and Rooth (2010)

[3] (PIAAC), also known as the Survey of Adult Skills, is a large-scale international study of key cognitive and workplace skills of adult (Flisil et al., 2016).

found that the wage penalty is large for both men and women ($P < 0.01$) and there was no evidence that individuals that were mismatched would move to a matched occupation over time. Occupational mismatch not only depresses the growth rate of wages in the current occupation but also stunts skills acquisition that decreases earnings in future occupations (Guvenen et al., 2020). In an analysis of the United States, Germany and France, Bol et al. (2019) found that higher earnings are associated with workers in occupations that match their level of education and field of study, however, the incremental earnings depend on the strength and clarity of the pathway between workers' educational qualification and the labour market.

There is a growing body of research that suggests a positive relationship between working in an occupation that is related to the field of study of a worker and various outcomes. For example, a study by Smith (2015) found that individuals who worked in occupations related to their field of study reported higher job satisfaction compared to those who did not ($p < .05$). In addition, research by Jones (2017) suggests that individuals who work in occupations related to their field of study may have higher levels of career advancement and progression. This is likely due to the fact that these individuals can utilize their education and training in a practical setting, which can lead to increased confidence and competence in their work. Another study by Williams (2019) found that workers who were employed in occupations related to their field of study reported higher levels of job security and stability compared to those who were not. This may be due to the fact that individuals who work in their field of study are more likely to have relevant skills and expertise that are in demand, leading to increased job opportunities and job retention. Overall, the research suggests that working in an occupation related to one's field of study can lead to increased job satisfaction, career advancement, job stability, and job security. These findings are important for both individuals seeking employment and for employers looking to maximize the potential of their workforce.

Guvenen et al. (2020) provided an empirical measure for the multidimensionality of skills mismatch, which was based on the difference between the set of skills required by a job and the set of abilities possessed by an employee for learning those skills to determine the factors that impact the productivity of a worker-occupation match. Using a US panel data on individuals and occupations and the skill mismatch measure, Guvenen et al. (2020) found that better matching of workers' abilities to their occupations can improve wages by 11% annually for the duration of an individual's career. South Africa has been affected by persistent skills shortages because of its political history and the restriction of opportunities in the labour market in the past. Skills shortages are found both in low-and high-skilled professionals in South Africa and occur when there is a lack of workers with specific skills or skilled workers exist but do not meet the employment criteria (Grapsa, 2017). The skills shortage has been worsened by skills mismatch which also negatively affects employability and successive labour market prospects faced by tertiary-educated individuals to a more extreme extent than for any other educational cohort (Van Broekhuizen, 2016). There are various measures of skills mismatch as it is conceptually broad. These measures include; using under-skilling, over-skilling, under-education and over-education to evaluate vertical mismatch; using hard-to-fill vacancies and unfilled vacancies to determine skill shortage; using skill gaps and lastly, using field of study mismatch to evaluate horizontal skills mismatch (McGuinness et al., 2018). A horizontal mismatch may be measured either with the use of questionnaires to ask the respondents to determine the degree to which their current occupation is related to the study field of their highest qualification or by comparing a variable for fields of study with occupation codes (McGuinness et al., 2018). This study evaluates horizontal mismatch using a comparison of a field of study variable with occupation code.

Job mismatch in South Africa

The skills mismatch within the South African economy occurs at three levels: demand mismatch, educational supply mismatch, and qualification-job mismatch (Arends et al., 2016). Demand mismatch, which is the most significant form of skills mismatch in South Africa, occurs when the types of jobs that are created do not match the skills set and expectations of the working-age population. Educational supply mismatch occurs when the skills demanded and the skills currently produced by the education system do not align (Arends et al., 2016 p. 74). The last form of skills mismatch found in South Africa, qualification-job mismatch, occurs when individuals are working in occupations and sectors not related to their tertiary education and training (Arends et al., 2016 p. 74)

In the recent Labour Market Intelligence Programme (LMIP) report on skills supply and demand in South Africa, Khuluvhe et al. (2022, p. 116) evaluated skills mismatches in SA using field-of-study mismatch, underqualification, and overqualification as the indicators and made comparisons for each form of mismatch with Turkey and Peru, as these countries have a similar socio-economic profile. They found that SA had the lowest level of field-of-study mismatch (32.5%) among the other two countries, Turkey (41.1%) and Peru (51.5%). Despite South Africa's encouraging statistics, it must be underlined that SA's figure implies that about one-third of individuals work in a profession not related to their field of study. Additionally, the study found that South Africa had a much larger percentage of underqualified people than the other two middle-income countries: 28.1%, as opposed to 9.3% and 14.0% in Peru and Turkey, respectively. However, compared to Turkey (29.1%) and Peru (26.3%), South Africa had the lowest frequency of overqualification (24.2%). The greatest skills shortage in South Africa was found in managers and professionals, two occupational groups that typically attract highly skilled workers (Khuluvhe et al., 2022, p. 116). Furthermore, 61.9% of industries are dealing with occupational shortages, with the most severe shortages occurring in the fields of insurance, public services, banking, finance, and education; sports, hospitality, tourism, the arts, and construction all experienced occupational surpluses.

Mncayi & Meyer (2022) study on underemployment in South Africa, based on graduates between the ages of 20 and 34 with at least a bachelor's degree, measured and evaluated underemployment based on income[4], time[5], and skills (field-based). The field-based definition of underemployment describes underemployment as working outside an individual's field of expertise, training, or education (Mncayi & Meyer, 2022). The study found that a large percentage of young graduates reported themselves as underemployed, irrespective of the type of underemployment. The results revealed that at least 45% of the sampled graduates reported themselves as underemployed. Likewise, Meyer & Mncayi (2021), when evaluating different aspects of underemployment, found that younger graduates aged 20–29 were more likely to be underemployed in comparison to their more mature counterparts, those aged between 30-34. Furthermore, the study showed that there was a higher likelihood of underemployment for unmarried graduates and graduates residing in rural areas; additionally, career guidance was found to significantly reduce the likelihood of being underemployed. Beaukes et al. (2017) used time-based and over-qualification methods to evaluate underemployment in South Africa. Using data from 2008–2016 QLFSs, 2000–2007 Labour Force Surveys (LFSs) and 1995–1999 October Household Surveys (OHSs), they discovered that 6–15% of workers were

[4]An employee's perception of income underemployment includes whether they believe they are paid inadequately in comparison to their previous employment or to those who possess comparable abilities, education, qualifications, and other traits (Mncayi & Meyer, 2022).

[5] Time underemployment refers to working fewer weekly hours than desired (involuntary part-time work) (Mncayi & Meyer, 2022).

underemployed when evaluated using the over-qualified approach, while 3–6% of employed people were underemployed using the time-based approach.

Graham, Williams, and Chisoro (2019) found that the barriers to the labour market for unemployed graduates in South Africa include a lack of relevant work experience, a lack of knowledge about effective job-searching strategies, a lack of social capital, and high costs associated with job searching. They further highlighted that the reality that South African graduates are not a homogenous group is concealed by the country's low graduate unemployment rate; moreover, rates of unemployment vary for various graduate categories, and there are clear variances in how well they transition into the labour market. Despite their qualifications, some graduates find it easier to obtain employment while others go through chronic unemployment (defined as being unemployed for more than 12 months) (Graham, Williams, & Chisoro, 2019). According to Baldry (2016), the year of graduation, socio-economic status, and race were the main predictors of unemployment among graduates. However, the field of study, level of study, grades earned, and whether or not graduates received career guidance at their higher education institution had no significant impact on graduates' employment or unemployed status. Moreover, the study found that of the observed employed graduates, 27% reported themselves as underemployed.

The majority of sub-Saharan African countries have poor institutional environments, insufficient labour demand to absorb the increased supply, and, most importantly, poor quality higher education, where the majority of the envisioned skills are not adequately covered in the curricula, taught, or tested during qualification examinations. These factors are typically the causes of qualification mismatches (Saurez Robles, 2022). Focusing on four countries—Uganda, South Africa, Kenya, and Benin—Saurez Robles (2022, p. 27) found that the rate of high-skilled over-qualification was highest in South Africa, with 30.1% of high-skilled workers with a tertiary education working in medium-skilled occupations. In Kenya and Benin, however, it was 26% and 17%, respectively. This means that a large number of university graduates in Sub-Saharan Africa are employed as clerks, salespeople, and in other non-graduate occupations. The findings from the works of literature suggest that even if South African graduates overcome the hurdles of unemployment, they may still face the burden of being mismatched or underemployed.

DATA

This study will be using sample survey data from the quarterly labour force survey for the period 2015-2019. The QLFS is a household-based sample survey that is administered by Statistics South Africa (Stats SA). Stats SA gathers data on the labour market activities of individuals aged 15 years or older who reside in South Africa. The Master Sample of the QLFS is intended to be inclusive of both metro and non-metro regions within each province in South Africa. The sample is further divided into geographical types within the metros. Urban, tribal, and farms are the three types of geography. This suggests that the sample within a metropolitan region is representative of the various geography types that can exist there. It is divided into four rotating groups, which are divided into equal subgroups or panels. Each of the rotation groups is created to have a distribution pattern similar to that of the entire sample. They range in number from one to four, and these numbers also represent the quarters of the year during which the sample for that particular group will be rotated. A stratified two-stage method is used for the sampling of the QLFS, with probability proportional to size (PPS) sampling of PSUs in the first stage, and sampling of dwelling units (DUs) in the second stage. A quarter of the sampled dwellings is rotated out of the sample for each quarter of the QLFS. New dwellings from the same PSU or the next PSU on the list are used to replace these dwellings. Therefore, for the four consecutive quarters, the sampled dwellings are expected to remain in the sample (Stats SA, 2019).

The sample weights were designed to take into account the original selection probabilities (design weights); weight trimming; non-response; excluded population from the sampling frame; adjustments for PSUs that were subsampled or segmented; and benchmarking to known population estimates from the Demographic Analysis Division within Stats SA. In the final stage of generating the sample weights, all household individuals are given the same adjusted base weight. For various age, race, and gender groups at the national level as well as at the level of individual metropolitan and non-metropolitan areas within the provinces, the adjusted base weights are calibrated so that the aggregate totals match with the independently derived population estimates (from the Stats SA Demographic Analysis Division). The calibrated weights are created with the restriction that each member of the same household should have the same calibrated weight, with a lower bound of 50. Imputation is typically used for non-response as well as invalid or inconsistent responses. Response and non-response are the two response types that can be applied to the eligible households in the sampled residences. To account for the families that did not answer, weight adjustment is used (e.g. refusal, no contact, etc.). PSU non-response and household non-response are used to compute the adjustment for total non-response (Stats SA, 2019).

For our analyses, we use the sampling weight provided in the QLFS. We restrict the sample to only consider individuals with tertiary/higher education as graduates. We define a graduate as a person holding a higher certificate, diploma or degree either from a University/Technikon/College. Furthermore, we focus on youth graduates between the ages of 25 and 34 as individuals below 25 are probably still furthering their education. and youth account for a large percentage of new entrants in the labour market. We also use non-youth graduates between the ages of 35 to 44 to make a comparison between youth graduates and account for working experience.

Using the information on the field of study and occupation for 2015 to 2019 from the QLFS. The grouped fields of study are presented in Appendix: Table A1 and the grouped field of occupation are in Appendix: Table A2. The grouped field of occupation is created using the occupation list and codes from the Statistics South Africa 2001 census. We focus on Commerce, STEM, Education and Health fields of study because of the relatively small number of observations for the other fields of study as tabulated in Appendix Table: A3 (i.e humanities, social science, law and agriculture). The grouping of qualifications has traditionally been done using the three Classification of Educational Subject Matter (CESM) categories: Humanities; Science, Technology, and Engineering; and Business, Commerce and Management Studies (Arends et al., 2016 p. 77). Hence, we group graduates that majored in Finance, Accounting, Economics, Marketing and Business Management in the Commerce field of study and the STEM grouped field of study contains graduates that hold qualifications in Science, Technology, Mathematics and Engineering. We could not evaluate Humanites graduates because of the relatively small number of observation, however, we include Education and Health graduates in our analysis.

The exclusion of the other fields of study risk that the final sample may not be a perfect representation of the total population of graduates in South Africa but rather a representation of occupational mismatch in the population of individuals who have invested in observed fields of study.

METHODOLOGY

Descriptive Table

To answer the first research question on job-education mismatch for different fields of study, descriptive tables are used to investigate graduates' occupational mismatch both vertically and horizontally.

Horizontal Mismatch Specification

An objective measure for horizontal mismatch that compares a field of study variable with occupation codes as specified by McGuinness (2018) is used for this study. We use graduates who work in professional, technical and associate professional occupations to compare their field of study to their current occupations for the determination of horizontal match or mismatch. The grouped fields of study are presented in Appendix: Table A1 and the grouped fields of occupation are in Appendix: Table A2. A graduate is considered to be horizontally mismatched if they are employed in an occupation that is not related to their field of study, and horizontally matched if they are employed in an occupation related to their field of study.

The limitations in evaluating horizontal mismatch are that we cannot account for unobservables. There may be unobserved selection into different occupation fields (and in employment more generally) and selection into fields of study. Furthermore, informal skills and training that may have been obtained through experiences in the labour market are not observed and these informal skills may likely relate more to the occupation than the person's main study field.

Vertical Mismatch Specification

Vertical mismatch can be measured subjectively or objectively. The subjective measure of vertical mismatch known as worker self-assessment is based on the worker's own subjective measure of job-education mismatch. Moreover, there are two common objective measures of vertical mismatch: realised matches and job evaluation (job analysis). The method of realised matches calculates the mean or median amount of education needed for a particular occupation, declaring workers with the required education below or above the average level as under or over educated (Mcguiness et al., 2018). The job evaluation approach identifies under- and over-education using the Classification of Occupations (ISCO), which classifies major occupational groups by level of education in accordance with the International Standard Classification of Education (ISCED).

This study applies the job evaluation method to evaluate vertical mismatch, following the works of Farooq (2011), Battu, et al. (2000), and Grapsa (2017). This study employs the job evaluation method using the Organising Framework for Occupations (OFO) 2012 which is a coded occupational classification system used by the Department of Higher Education and Training (DHET) to identify, report and monitor skills demand and supply in the South African labour market. The grouping of occupations is based on two skill dimensions, skill level, and skill specialisation. Table 1 provides the OFO final classification of major occupation groups and their relative skill level.

Table 1: Classification of major occupation groups with their associated skill level

Major Group	Skill Level
1. Legislators, senior officials and managers	3 + 4
2. Professionals	4 (Degree)
3. Technicians and associate professionals	3 (Diploma/Certificate)
4. Clerical Support Workers	2 (Secondary Education)
5. Service and sales workers	2 (Secondary Education)
6. Skilled agricultural and fishery workers Craft and related trades workers	2 (Secondary Education)
7. Plant and machinery operators and assemblers	2 (Secondary Education)
8. Elementary occupations	1 (Primary Education)

Source: DHET (2012)

For this study, graduates are defined as vertically matched if their highest qualification obtained is equivalent to the skill level required in their current occupation. Moreover, if the highest qualification they obtained is above the skill level required in their current occupation, then such graduates are defined as over-educated, lastly, if the highest qualification obtained is below the skill level required in their current occupation, such graduates are defined as under-educated. The limitations of using job analysis as a measure of vertical mismatch stem from the strong assumptions required. The use of qualifications as a proxy to measure an individual's skills and knowledge relies on the assumption that relevant knowledge and skills are acquired through formal education, disregarding skills obtained in other life domains such as on-the-job training and family interactions (Capsada-Munsech, 2019). Furthermore, qualifications assume no skill variability among individuals, resulting in the same level of skills across different fields of study (Capsada-Munsech, 2019).

Multinomial Logit Regression Methodology

To investigate the likelihood of being employed in a matched occupation conditioned on the field of study we use a multinomial logistic regression. Multinomial logistic regression is an appropriate model used when evaluating a categorical dependent variable with more than two categories. The strengths of a multinomial logistics regression are that it does not assume homoscedasticity, linearity or normality. Salsa-Velasco (2021) also used multinomial logistic regression to determine the match status of Spain graduates. Multinomial logit (MNL) and Multinomial probit (MNP) are the two commonly used models when dealing with a categorical dependent variable. MNL is easier to interpret with straightforward interpretations, however, the major concern with MNL is the assumption of independence of irrelevant alternatives (IIA) (Cheng & Long, 2007). Similar to the assumption of independent error terms in the linear regression model, the IIA property implies that variables excluded from the model are independent random variables (Cheng & Long, 2007).

Moreover, the advantage of MNP over MNL is that it does not assume independence of irrelevant alternatives (IIA) (Cheng & Long, 2007). MNP is capable of relaxing the IIA assumption by specifying correlated latent–variable errors while allowing for heteroskedastic latent-variable errors and alternative-specific independent variables. Kropko (2007) study on choosing multinomial logit and multinomial probit models for the analysis of unordered choice data suggested that a multinomial logit is almost always better than a multinomial probit even when IIA is violated. In addition, IIA is not of great concern for a small number of categories. Hence, the use of multinomial logistic regression with coefficients as relative risk ratios for this study.

Multinomial Logit Model Specification

The MLN takes into account the probability of a certain event occurring as:

$$Prob(Y_i = k) = \frac{\exp\,(\mathrm{X}'\beta_k)}{\sum_{j=1}^{4} \exp\,(X'\beta_j)} \qquad Eq(1)$$

Our response variable has four categorical outcomes that have an unordered structure: fully matched, horizontal mismatch, overqualified, and not employed, therefore, k = 1,2,3,4 respectively. This model provides the probability that an individual with X characteristics is in outcome k. In this study, the explanatory variable of interest is the fields of study and several control variables related to employment are also included in the regression. The base category is not employed ($\beta_4 = 0$), and the probability of the kth outcome relative to the base outcome is defined as:

$$Prob(Y_i = k) = \frac{\exp\,(X'\beta_k)}{1 + \sum_{j=1}^{3} \exp\,(X'\beta_j)}\ if\ k = 1,2,3 \qquad Eq(2)$$

Estimated Equation

$$\log(\text{odds}) = \ln\left(\frac{P}{1-P}\right) = \alpha + \lambda_i Field_{it} + \lambda_{it} X_{it} \qquad Eq(3)$$

The response variable (occupation status) has four categorical outcomes: fully matched, horizontal mismatch, overeducated and not employed. P is the probability of being in a particular occupation status category. Field represents the categorical field of study variable as the variable of interest where λ is the estimated coefficient of the relative risk ratio of each category relative to the base category. X represents a set of variables related to employment namely, age, gender, marital status, population group and metro. α is the constant of the model. The reference outcome variable is not employed which accounts for the unemployed, discouraged work seekers and those who are not economically active

Mincerian OLS regression Methodology

Earnings Regression

To determine the association between being mismatched and earnings conditioned on graduates' field of study, we run individual Mincerian OLS wage regressions for each grouped field of study. As of 2010, Statistics South Africa reports the income data from the QLFS in an annualised dataset named Labour Market Dynamics in South Africa (LMDSA). Therefore, for the earnings regression, we use the income data from the LMDSA for the period 2015-2019.

To account for the two types of mismatch, vertical (overeducation) and horizontal, we create a categorical variable, *Match*. *Match* is a categorical variable equal to 1 if the individual is fully matched (both vertically and horizontally matched), 2 if the individual is horizontally mismatched and 3 if the individual is vertically mismatched. The model is specified as:

$$\ln(W_{it}) = \delta_0 + \delta_1 Match_{it} + \delta X_{it} + \mu_{it} \qquad Eq(4)$$

$\ln(W_{it})$ represents the natural logarithm of hourly wages which is the independent variable. The logarithm of hourly wages is used instead of monthly earnings to avoid the overestimation of the wage gap. The data does not include hourly wages therefore the variable is generated by dividing real monthly earnings by hours worked monthly. We calculate monthly hours by multiplying the hours worked by the average weeks in a month. We use 4.25 as the average week in a month. *Match* is a categorical variable representing the job-education match status and *X* represents a vector of covariates that contains observable individual characteristics and job characteristics such as age, marital status, gender, race, the highest level of education, industry, sector, firm size and metro.

Tenure Regression

We acknowledge that some control variables such as sector and industry may be considered as "bad controls". Cinelli, Forney & Pearl (2022) explained that bad controls are variables that themselves can also be outcome variables (i.e. they may also be dependent variables). There are studies in the literature that use these controls and this is why we chose to use them, for instance, Casale & Posel (2011) study on unions and the gender wage gap in South Africa included job tenure and employment sector in their OLS earnings regression. Ntuli & Kwenda (2014) also controlled for sector and location dummies.

Given that job tenure is a bad control we estimate it independently to determine the association between being mismatched and job tenure.

$$Tenure_{it} = \theta_0 + \theta_1 Match_{it} + \theta X_{it} + \mu_{it} \qquad Eq(5)$$

Tenure is the independent variable representing job tenure. *Match* is a categorical variable representing the three mis(match) categories (full match, horizontal mismatch and vertical mismatch) and *X* is a set of covariates associated with job tenure.

The description of variables with survey questions is provided in Appendix Table A3.

Limitations

The limitations of this study are that we cannot control for unobservable selection into fields of study and fields of occupation. Unobserved characteristics can also lead to selection bias. Unobserved characteristics are characteristics such as attitudes or personality traits that are excluded in the data. If these characteristics are not taken into consideration, the selection process may be influenced and result in selection bias. For instance, if a study just collects information on gender and educational level without accounting for personality traits or attitudes, the findings may be biased as a result of the influence of these unreported variables. Existing works of literature deal with selection bias on unobservables by using methods such as instrumental variables. Instrumental variables are variables that are correlated with the outcome of interest but are not affected by the unobserved characteristics. By using these methods, researchers can reduce the influence of selection bias on unobservables and improve the accuracy of their results. Unfortunately, we cannot address them in this study.

DESCRIPTIVE STATISTICS

Sample Descriptives

The sample used for this study consists of 43 445 observations from the defined fields of study (Commerce, Education, Health and STEM). Among this sample, youth account for 55.19% of the graduates and 53.85% of the graduates are females. To evaluate job-education mismatch, the sample is limited to employed graduates from the defined fields of study. Therefore reducing the sample size to 32 959. Among this sample of employed graduates, 50.04% are youth and females make up 51.49% of the sample. The majority of the sample is African/Black (68.05%) followed by White (19.42%), Coloured (5.39%) and lastly Indian/Asian (5.39%). Table A5 in the Appendix provides the sample characteristics between youth and non-youth.

Observing each field of study individually and by age group reduces the number of observations for each field of study, thus making the sample size for each field of study not large enough to be perfectly representative of the population.

Descriptive Analyses

The tables below present descriptive analyses of the observed fields of study. Table 2 provides the employment status of youth graduates for the observed fields of study. We find that STEM and Commerce graduates have the lowest employment rates with 68.04% and 68.71% respectively. Moreover, Education graduates have the highest employment rate (78.93%) followed by Health graduates with an employment rate of 72.89%. Bhorat et al. (2017) found that in South Africa, individuals in the faculties of Science, Engineering, and Technology are significantly less likely to be employed than those in Health and Education. The high employment probabilities of graduates in the Education and Health fields may be associated with the large number of employment opportunities in the public sector for these fields (Bhorat et al., 2017). This is evident in Figure 1, whereby we see that the majority (69.12%) of youth Education graduates are employed in the public sector, while 51.69% of Health graduates are also employed in the public sector. However, the majority of Commerce (78.6%) and STEM (79.61%) youth graduates are employed in the private sector.

When observing non-youth employment status (Table 3), we find that, on average, about 85% of these graduates are employed. This depicts the current stance of the labour market in South Africa, whereby the youth suffer the brunt of unemployment. Similarly to youth graduates, we see in Figure 2 that Education and Health non-youth graduates work mostly in the public sector (77.58% and 55.34%, respectively). Moreover, the majority of Commerce (73.31%) and

STEM (74.5%) graduates work in the private sector. The Pearson X2 shows a statistically significant association between the fields of study and employment status for both age groups.

Table 2: Youth employment status for each field of study

Youth Employment Status	Grouped fields of study				
	Commerce	Education	Health	STEM	Total
Employed	**68.71**	**78.93**	**72.89**	**68.04**	**69.96**
	[67.15,70.24]	[76.35,81.3]	[70.11,75.5]	[66.53,69.52]	[69,70.91]
	6142	1974	1956	6421	16493
Unemployed	**21.78**	**13.98**	**17.54**	**22.98**	**20.99**
	[20.53,23.09]	[12.1,16.11]	[15.45,19.85]	[21.73,24.28]	[20.21,21.8]
	2084	357	478	2365	5284
Not Economically Active	**9.505**	**7.091**	**9.571**	**8.977**	**9.044**
	[8.591,10.51]	[5.726,8.75]	[8.022,11.38]	[8.153,9.875]	[8.492,9.628]
	872	180	254	893	2199
Total	**100**	**100**	**100**	**100**	**100**
	9098	2511	2688	9679	23976
Pearson Uncorrected chi2(6) = 1207.7514 P = 0.0000					

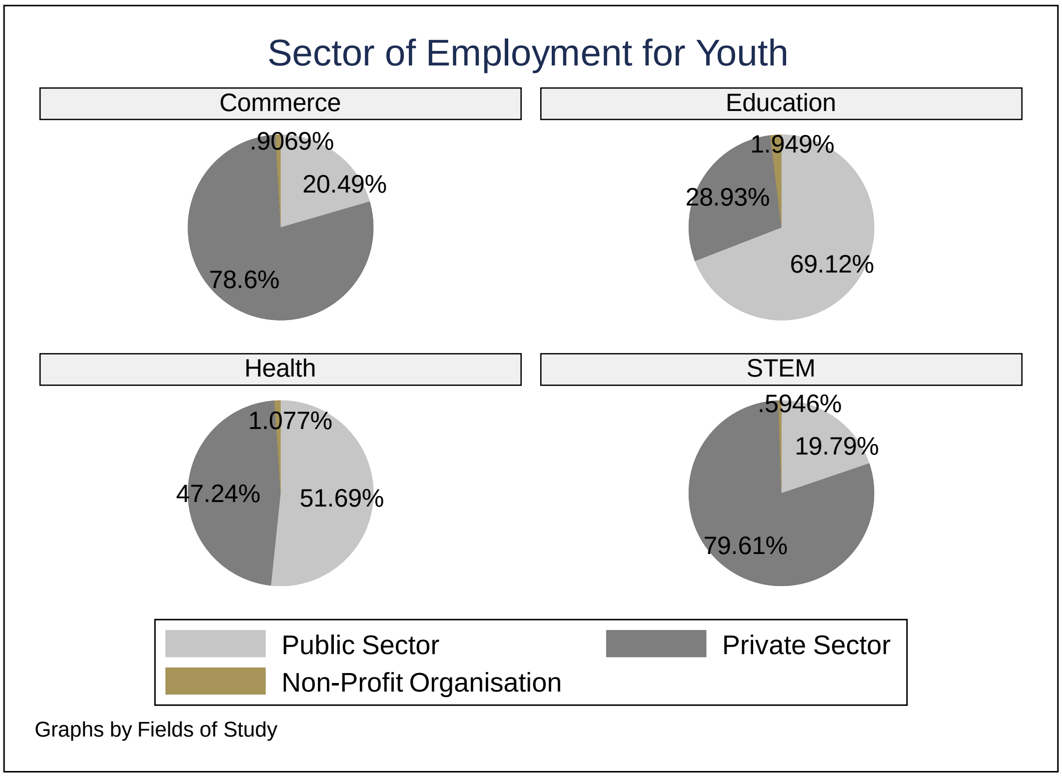
Note: Data are weighted using sampling weights. 1st row percentage, 2nd row 90% confidence interval in brackets, 3rd row number of observations.

Table 3: Non- Youth employment status for each field of study

Non-Youth Employment Status	Grouped fields of study				
	Commerce	Education	Health	STEM	Total
Employed	**84.28**	**89.05**	**86.39**	**83.5**	**85.12**
	[82.85,85.62]	[87.27,90.6]	[84.06,88.43]	[81.98,84.92]	[84.27,85.94]
	5668	3323	2200	5275	16466
Unemployed	**10.76**	**6.258**	**8.399**	**12.19**	**10.15**
	[9.69,11.93]	[5.159,7.572]	[6.892,10.2]	[10.99,13.49]	[9.495,10.84]
	805	238	231	803	2077
Not Economically Active	**4.959**	**4.692**	**5.207**	**4.314**	**4.728**
	[4.208,5.835]	[3.701,5.933]	[3.901,6.919]	[3.588,5.18]	[4.254,5.251]
	361	161	124	280	926
Total	**100**	**100**	**100**	**100**	**100**
	6834	3722	2555	6358	19469
Pearson: Uncorrected chi2(6) = 1373.8098 P = 0.0000					

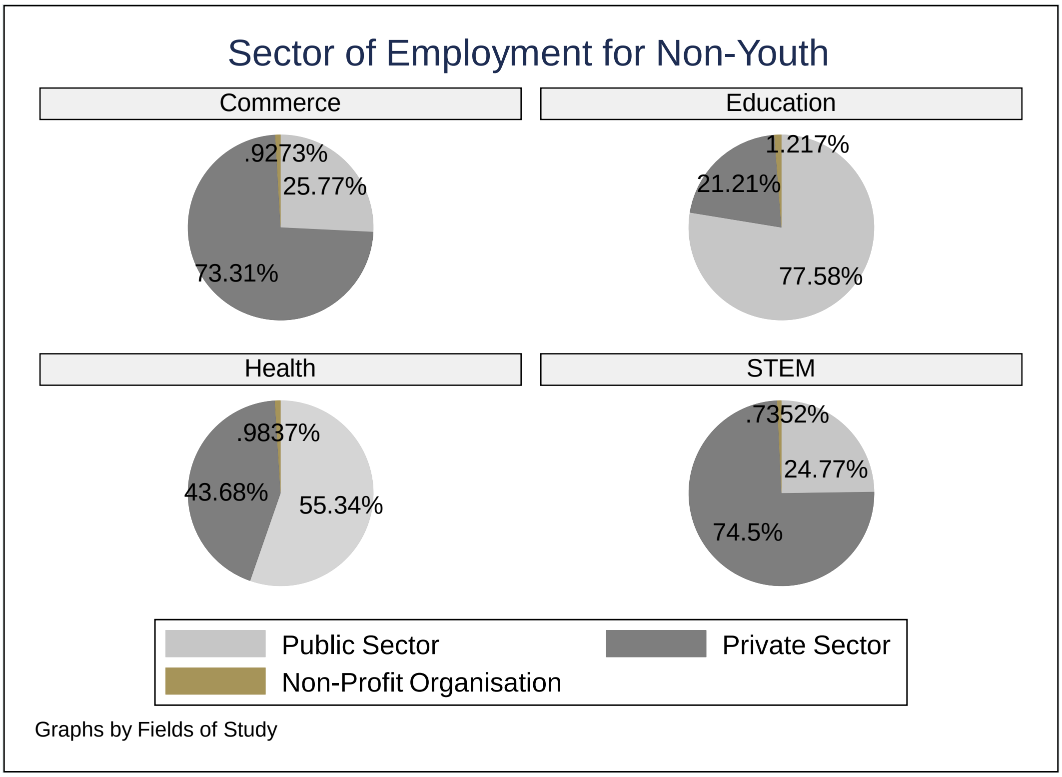
Note: Data are weighted using sampling weights. 1st row percentage, 2nd row 90% confidence interval in brackets, 3rd row number of observations.

Figure 1: Youth Sector of Employment by Field of Study



Note: Data are weighted using sampling weight

Figure 2: Youth Sector of Employment by Field of Study



Note: Data are weighted using sampling weight

Average hourly wages

The two-sample t-test results for the difference in average hourly wages between the two age groups conditioned on their job-education mis(match) status found that for Commerce graduates, there is no statistically significant difference in the average hourly wages between the age groups when graduates are horizontally mismatched. However, there is a statistically significant difference in the average hourly wages between the age groups when graduates are fully matched or overeducated. Moreover, for STEM graduates, there is no statistically significant difference in hourly wages between the age groups when graduates are fully matched or horizontally mismatched. However, there is a statistically significant difference in average hourly wages between youth and non-youth graduates when these graduates are overeducated for their occupations.

The results may be biased due to missing earnings data. Appendix Table A4 shows that we lost 1581 observations for Commerce graduates and 1702 observations for STEM graduates.

Table 4: Two-sample t test for earnings with equal variances

	obs1	obs2	Mean1	Mean2	diff	St Err	t value	p value
Commerce								
Fully Matched	502	449	72.76	79.55	-6.80	3.26	-2.1	0.037
Horizontal Mismatch	513	464	61.48	66.68	-5.19	3.03	-1.7	0.087
Overeducated	2465	1739	40.66	46.98	-6.32	1.21	-5.2	0.000
STEM								
Fully Matched	1163	820	77.01	78.89	-1.88	2.36	-0.8	0.427
Horizontal Mismatch	489	437	74.63	76.19	-1.57	3.26	-0.5	0.632
Overeducated	2688	1909	45.23	50.75	-5.52	1.31	-4.2	0.000

Note: 1 refers to youth and 2 refers to non-youth

Average Tenure

The difference in average job tenure between the age groups (reported in quarters) conditioned on graduates job-education mis(match) found that there is a statistically significant difference in job tenure between the two age groups regardless of graduates being matched or mismatched. For youth graduates, horizontally mismatched graduates have the shortest average tenure of approximately 3 years (12.7 quarters). Moreover, the average tenure for non-youth graduates that are matched or mismatched is slightly similar, with an average of about 7 years. It is expected that older individuals are more likely to stay in the same job in comparison to young adults.

Table 5: Two-sample t test for job tenure with equal variances

	obs1	obs2	Mean1	Mean2	diff	St Err	t value	p value
Commerce								
Fully Matched	267	209	15.31	28.14	12.83	1.45	-8.85	0.000
Horizontal Mismatch	253	185	12.71	28.47	15.75	1.41	-11.15	0.000

Overeducated	1088	724	13.29	28.33	15.04	0.74	-20.35	0.000
STEM								
Fully Matched	570	357	16.42	29.98	-13.56	1.09	-12.45	0.000
Horizontal Mismatch	217	189	12.77	28.42	15.64	1.59	-9.9	0.000
Overeducated	1190	812	14.41	27.56	13.15	0.72	-18.3	0.000

Note: 1 refers to youth and 2 refers to non-youth

RESULTS

Job-Education Mismatch by Fields of Study

The tables below provide the cross-tabulation results for assessing job-education mismatch among graduates from the defined fields of study for both age groups. When observing horizontal mismatch, Table 6 shows that among youth graduates, the Commerce field of study has the highest percentage of graduates working in horizontally mismatched occupations (39.21%), followed by STEM graduates with 26.07%, then Health graduates with 16.97%, and, lastly, Education graduates with only about 6.04% being horizontally mismatched. Education graduates are limited to teaching as an occupation, which may explain how well matched (horizontally) they are to their occupation. Furthermore, Health graduates are better matched to their occupation because the skills and knowledge they acquire are more occupation-specific than general skills. Graduates from fields that provide more specialised human capital, such as medicine, are less likely to be horizontally mismatched than graduates from fields that produce more broad human capital, such as the Social Sciences, Commerce, and Law (Rudakov et al., 2019). Moreover, STEM graduates possess a variety of skills that enable them to work in different industries (Arends et al., 2016, p. 83). Reddy et al. (2016) found that many Science and Engineering graduates in South Africa choose to work in the financial industry. Likewise, Arends et al. (2016, p. 80) also found that a significant number of Science and Engineering graduates from both higher and technical vocational institutions in South Africa prefer to work in the financial services industry rather than the manufacturing industry. Hence, this may explain the level of STEM graduates that is horizontally mismatched in the provided result. These results are similar for non-youth graduates (Table 7), which suggests that the likelihood of leaving a horizontally mismatched occupation is slim and driven by work experience. As an individual gains working experience in a particular occupation, it increases the probability of them working in the same field of occupation in the future.

Table 6: Percentage of youth graduates in horizontal mis(match) occupation

Youth	Grouped fields of study				
	Commerce	Education	Health	STEM	Total
Horizontal Match	**60.79**	**93.96**	**83.03**	**73.93**	**76.26**

	[57.28,64.2]	[92.25,95.31]	[79.56,86.02]	[71.16,76.51]	[74.71,77.75]
	1141	1518	1262	1946	5867
Horizontal Mismatch	**39.21**	**6.038**	**16.97**	**26.07**	**23.74**
	[35.8,42.72]	[4.687,7.745]	[13.98,20.44]	[23.49,28.84]	[22.25,25.29]
	777	92	232	694	1795
Total	**100**	**100**	**100**	**100**	**100**
	1918	1610	1494	2640	7662
Pearson Uncorrected chi2(3) = 13500 p = 0.0000					

Note: Data are weighted using sampling weights. 1st row percentage, 2nd row 90% confidence interval in brackets, 3rd row number of observations.

Table 7: Percentage of non-youth graduates in horizontal mis(match) occupation

Non-Youth	Grouped Field of Study				
	Commerce	Education	Health	STEM	Total
Horizontal Match	**60.66**	**93.29**	**85.37**	**71.11**	**78.59**
	[56.88,64.32]	[91.71,94.58]	[82.26,88.01]	[67.85,74.17]	[77.12,79.99]
	1004	2568	1432	1375	6379
Horizontal Mismatch	**39.34**	**6.714**	**14.63**	**28.89**	**21.41**
	[35.68,43.12]	[5.421,8.288]	[11.99,17.74]	[25.83,32.15]	[20.01,22.88]
	672	168	228	600	1668
Total	**100**	**100**	**100**	**100**	**100**
	1676	2736	1660	1975	8047
Pearson Uncorrected chi2(3) = 24400 p = 0.0000					

Note: Data are weighted using sampling weights. 1st row percentage, 2nd row 90% confidence interval in brackets, 3rd row number of observations.

The tables below provide the two-way tabulation results for evaluating vertical mismatch. From Table 8, we find that the majority of youth Commerce (52.73%) and STEM (51.37%) graduates are overeducated for their occupations, while 26.13% of Education graduates and 32.62% of Health graduates are also overeducated. Generally, there is only a small percentage of graduates who are undereducated in their occupation. Moreover, when comparing the level of vertical mis(match) between youth and non-youth graduates, we find that non-youth graduates (Table 9) are more vertically matched than youth graduates. It could be that as individuals gain work experience, they advance in their careers. However, there is still a large percentage of Commerce (41.22%) and STEM (42.72%) graduates that are overeducated for their occupation.

The high rate of vertically mismatched graduates depicts an imbalance in the demand and supply of labour. The inability of the formal sector to create high-skilled jobs that match the number of tertiary graduates entering the labour market has been highlighted as contributing to the rate of overeducation in sub-Saharan Africa (Saurez, 2022). Work experience has also been found to hinder graduates from securing suitable employment. Mncayi & Meyer (2022) found that young workers with limited working experience were frequently overeducated for their occupation in South Africa.

According to Habiyaremye, Habanabakize, & Nwosu (2022), developing non-technical skills increases one's chances of landing stable employment more than developing technical skills. They emphasised the value of soft skills in increasing employability and lowering the degree of vertical skill mismatch. The PwC's 2022 Global Survey found that besides having practical, technical, or hard skills such as educational qualification, soft skills such as conflict resolution, problem-solving, creative thinking, and leadership are of utmost importance for employability (BusinessTech, 2022). This suggests that having the relevant qualifications for a job is not enough to secure a suitable position; there is a growing labour demand for individuals who possess not just technical skills but also soft skills.

Table 8: Percentage of youth graduates in vertical mis(match) occupation

Youth	Grouped fields of study				
	Commerce	Education	Health	STEM	Total
Vertical Match	**43.17**	**69.4**	**64.81**	**43.95**	**49.33**
	[41.09,45.27]	[66.15,72.46]	[61.46,68.01]	[41.98,45.95]	[48.07,50.6]
	2254	1363	1263	2565	7445
Over-education	**52.73**	**26.13**	**32.62**	**51.37**	**46.47**
	[50.62,54.82]	[23.17,29.32]	[29.44,35.98]	[49.34,53.4]	[45.2,47.75]
	3102	503	641	3258	7504
Under-education	**4.104**	**4.471**	**2.57**	**4.674**	**4.193**
	[3.422,4.916]	[3.323,5.992]	[1.766,3.724]	[3.931,5.549]	[3.748,4.689]
	234	88	52	273	647
Total	**100**	**100**	**100**	**100**	**100**
	5590	1954	1956	6096	15956
Pearson: Uncorrected chi2(6) = 8107.2573 p = 0.0000					

Note: Data are weighted using sampling weights. 1st row percentage, 2nd row 90% confidence interval in brackets, 3rd row number of observations.

Table 9: Percentage of non-youth graduates in vertical mis(match) occupation

Non-Youth	Grouped fields of study				
	Commerce	Education	Health	STEM	Total
Vertical match	**54.33**	**78.29**	**69.13**	**52.11**	**60.23**
	[52.07,56.57]	[76.17,80.27]	[65.98,72.12]	[49.9,54.32]	[58.96,61.48]
	2717	2595	1508	2458	9278
Over-education	**41.22**	**17.15**	**26.6**	**42.72**	**35.09**
	[39.01,43.47]	[15.35,19.12]	[23.71,29.7]	[40.53,44.94]	[33.87,36.34]
	2243	564	605	2306	5718

Under-education	**4.449**	**4.555**	**4.265**	**5.166**	**4.678**
	[3.666,5.388]	[3.61,5.732]	[3.201,5.663]	[4.29,6.209]	[4.193,5.216]
	232	141	87	240	700
Total	**100**	**100**	**100**	**100**	**100**
	5192	3300	2200	5004	15696
Pearson: Uncorrected chi2(6) = 12400 p = 0.0000					

Note: Data are weighted using sampling weights. 1st row percentage, 2nd row 90% confidence interval in brackets, 3rd row number of observations.

Overall, when observing job-education mismatch, we find that graduates from the defined fields of study are more vertically mismatched in the form of overeducation than horizontally mismatched. Furthermore, among the four fields of study observed, Commerce and STEM graduates are more prone to being mismatched vertically as well as horizontally. The Pearson X^2 shows a statistically significant association between the fields of study and job-education mis(match).

Multinomial Logistic Regression

The multinomial logit regression results are reported in terms of relative risk ratio, with not employed as the base outcome category and Commerce as the reference category for the field of study explanatory variable. The multinomial logistic regression result found that graduates from Education, Health and STEM are significantly more likely to be employed in a fully matched occupation than not employed when compared to Commerce graduates. Moreover, Commerce graduates are significantly more likely to be overeducated for their occupation than not employed in comparison to the other observed fields of study. The result also found that Education graduates are significantly less likely to work in a horizontally mismatched occupation than to not be employed in comparison to Commerce graduates.

The reported result found that STEM graduates are more likely to be horizontally mismatched than not employed when compared to Commerce graduates, though the reported coefficient was statistically insignificant. Similar to the descriptive table results, these findings provide supporting evidence that youth Commerce and STEM graduates are more likely to transition into a mismatched occupation, with STEM youth graduates more likely to be horizontally mismatched while Commerce youth graduates are more likely to be vertically mismatched in the form of overeducation.

Table 10: Youth graduate multinomial logistic regression result for the likelihood of being employed in a mis(match) occupation.

	Full Match	Horizontal Mismatch	Vertical Mismatch

Field of study: Reference category= Commerce			
Education	6.507***	0.543***	0.787**
	(0.744)	(0.092)	(0.082)
Health	5.794***	1.055	0.730***
	(0.662)	(0.158)	(0.072)
STEM	2.437***	1.068	0.888**
	(0.209)	(0.112)	(0.051)
Observations	20,795	20,795	20,795
Wald chi2(159) = 71787.06 p=0.0000			

*Note: Controlled for gender, race, age, age squared, marital status, highest education level, metro and quarter-year dummies. The base category is Commerce. Standard errors are presented in parentheses and are clustered at the individual level. ***p < 0.01, **p < 0.05, *p < 0.10*

Earnings Regression Results

To evaluate the association between earnings and job-education mismatch, we observe only Commerce and STEM graduates because, as shown in the descriptive table, they have the highest rate of mismatched graduates. The Mincerian OLS earnings regression results (Table 11) for STEM and Commerce graduates found that there is a statistically significant negative association between earnings and being overeducated for an occupation for both age groups. Overeducated youth Commerce graduates receive about 28.7% less in hourly wages than Commerce graduates who are fully matched, while STEM youth graduates who are overeducated for their occupation receive approximately 27.7% less in hourly wages than fully matched STEM graduates. The wage penalty associated with being overeducated is expected, as these graduates are mostly working in non-graduate occupations (i.e., clerks, sales personnel, machine operators, etc.).

The results also found that for Commerce graduates, the association between earnings and being horizontally mismatched is different between the two age groups. Commerce youth graduates experience a wage gain from being horizontally mismatched; however, non-youth Commerce graduates experience a wage penalty when they are horizontally mismatched. However, the reported coefficients were not statistically significant. For STEM graduates, the results found a statistically significant positive association between earnings and being horizontally mismatched. STEM graduates from both age groups experience a wage gain from being horizontally mismatched. The result found that STEM youth graduates receive 17.4% more in hourly wages when they are horizontally mismatched than when they are well-matched in their occupation, whereas non-youth STEM graduates receive 21.9% more in hourly wages. The wage gain for STEM graduates who are horizontally mismatched may be a contributing factor to their not working in their related field of occupation. Furthermore, linking this result to the evidence of a large number of STEM graduates working in the financial industry as opposed to working in the manufacturing industry (Arends et al., 2016) suggests that the financial industry may be a better employer than the manufacturing industry.

Overall, the findings from the regression results show that there is a wage penalty for being overeducated in an occupation in both fields of study. Moreover, the difference in the wage effect of horizontal mismatch between graduates highlights the heterogeneity among graduates from different fields of study. This provides supporting evidence that graduates are not homogeneous and experience different labour market outcomes. Hence, it is paramount that when researching the labour outcomes of graduates, graduates from different fields of study should be observed independently. Moreover, we note that these results may be biased due to the missing earnings data.

Table 11: Youth and Non-Youth Mincerian OLS Earnings Regression Results

	Youth		Non-Youth	
	Commerce	Stem	Commerce	Stem
VARIABLES	Ln(wage)	Ln(wage)	Ln(wage)	Ln(wage)
Horizontal Mismatch	0.086	0.174*	-0.114	0.219**
	(0.099)	(0.092)	(0.126)	(0.110)
Overeducated	-0.287***	-0.277***	-0.339***	-0.242***
	(0.084)	(0.067)	(0.103)	(0.090)
Observations	3,231	3,929	2,327	2,717
R-squared	0.266	0.273	0.266	0.277

*Note: Controlled for gender, race, age, age squared, marital status, highest education level, metro and quarter-year dummies. The base category is Commerce. Standard errors are presented in parentheses and are clustered at the individual level. ***p < 0.01, **p < 0.05, *p < 0.10*

Job Tenure Result

Table 12 below provides the OLS regression results for job tenure reported in quarters. The results found that there is a statistically significant negative association between job tenure and being horizontally mismatched for youth graduates. Youth graduates from both fields of study experience shorter tenure when they are horizontally mismatched in comparison to when they are fully matched to their occupation. The results show that Commerce graduates who are horizontally mismatched experience approximately 9 months less in tenure, while STEM graduates who are horizontally mismatched experience approximately 6 months less in tenure when compared to those who are fully matched. The theory of job search states that mismatched employees may try to improve their fit by changing occupations until they find an optimal match (Somers et al., 2019). This theory is evident among horizontally mismatched youth graduates. Furthermore, the results show that overeducated graduates also experience shorter tenure; however, the reported coefficients were insignificant, and the difference in tenure is about 3 months less than for fully matched graduates.

When comparing the results of the two age groups, we find that, unlike youth Commerce graduates, horizontally mismatched non-youth Commerce graduates experience longer tenure, though the reported coefficient is insignificant. This suggests that older Commerce graduates that are mismatched tend to settle in the same job longer than Commerce graduates that are matched. Generally, the difference in job tenure between matched graduates and mismatched graduates is small, especially for overeducated graduates. The lack of sufficient employment opportunities in the country can hinder workers from leaving their current employer, even when they are not completely satisfied with their job.

Table 12: Youth and Non-Youth Mincerian OLS Regression Result for Job tenure

	Youth		Non-Youth	
	Commerce	Stem	Commerce	Stem
VARIABLES	Job tenure	Job tenure	Job tenure	Job tenure
Horizontal Mismatch	-2.782***	-2.132**	2.309	-1.391
	(0.937)	(0.911)	(1.757)	(1.620)
Overeducated	-1.208	-0.999	1.881	-0.014
	(0.768)	(0.647)	(1.448)	(1.058)
Observations	4,097	4,877	3,001	3,438
R-squared	0.352	0.335	0.279	0.326

*Note: Controlled for gender, race, age, age squared, marital status, highest education level, metro and quarter-year dummies. The base category is Commerce. Standard errors are presented in parentheses and are clustered at the individual level. ***p < 0.01, **p < 0.05, *p < 0.10*

CONCLUSION

This study aimed to provide insight into South African graduates' labour market outcomes by evaluating job-education mismatch both vertically and horizontally conditioned on graduates' fields of study. We made comparisons between two age groups: youth graduates between the ages of 24 and 34, and non-youth graduates between the ages of 35 and 44. Furthermore, the study focused on graduates from the fields of Education, Commerce, Health, and STEM. Using descriptive tables, we found that Commerce (39.21%) and STEM (26.07%) youth graduates have the highest rate of horizontal mismatch. Likewise, these graduates also reported the highest percentage of vertical mismatch in the form of overeducation: 52.73% for Commerce graduates and 51.37% for STEM graduates. Moreover, Education and Health youth graduates had the lowest rate of mismatch. These results were similar to those of non-youth graduates except for the rate of overeducation, which was about 10% lower for non-youth graduates.

Furthermore, the estimated result of the multinomial logistic regression found that Commerce graduates are more likely to transition into an occupation that they are overeducated for when compared to the other fields of study (Health, Education, and STEM), while STEM graduates are more likely to transition into a horizontally mismatched occupation in comparison to the other fields of study. This study also evaluated the association between earnings and job-education mismatch as well as the association between earnings and job tenure using a Mincerian OLS regression. The result of the earnings Mincerian OLS regression found that there is a statistically significant negative association between being overeducated and earnings for both age groups. Commerce and STEM youth graduates experience a wage penalty of 28.7% and 27.7%, respectively, when working in an occupation that they are overeducated for. Lastly, the study found a statistically significant negative association between job tenure and youth graduates that are horizontally mismatched.

Limitations

There were a number of limitations for this study. Firstly, there are unobservable selection into fields of study and fields occupation that cannot be accounted for. Secondly, the sample size was not large enough to be perfectly representative of the total population of graduates in South Africa. Lastly, the substantial missing earnings data risk the earnings results being biased. The QLFS data, along with the LMDSA earnings data, have been criticised regarding the capture of earnings and employment data. Several measurement problems have been identified by Kerr and Wittenberg (2017; 2020) regarding the QLFS data. They explained how these issues hamper the examination of earnings and employment trends, which then negatively affect one's ability to analyse certain labour market issues, like trends in income inequality

Policy Implication

The findings from this study suggest a valuable loss in human capital as a result of the substantial rate of mismatches among graduates. Occupational mismatch leads to the underutilisation of human capital acquired from higher education and the economy suffers from a loss of output that could have been generated by reallocating genuinely mismatched workers to higher productive jobs (Cedefop, 2010). There needs to be greater collaboration between businesses and education institutions to reduce the gap between labour demand and labour supply. Businesses need to play a significant role in career pathways and qualification curricula to ensure that graduates acquire skills that are demanded in the labour market. Focusing on the supply side of the labour market will ensure that graduates have the necessary skills to meet the demands of the labour market, starting with the basic education curriculum. In the absence of such changes, mismatches will persist and be concealed by increased access to higher education and low graduate unemployment rates. Furthermore, career guidance is also essential in reducing job-education mismatch. The Labour Market Intelligence Programme provides report on skills demand and supply in South Africa biennially and this is published by the Department of Higher Education and Training (DHET). The DHET also publishes technical report on the critical skills list. These reports can be helpful for career guidance and need to be distributed and discussed with high school learners before pursuing their higher education studies. This will help foster better informed career decisions.

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APPENDIX

Table A1: Grouped Fields of Study

Grouped Fields of Study	
Commerce	Business, commerce and Management
	Finance, economics and accounting
	Management
	Marketing
Education	Education, Training or Development
STEM	Computer Science
	Engineering
	Information Technology
	Life Sciences
	Mechatronics
	Mathematics
	Physical Science
Health	Life Science
	Health care or Health Sciences
Other	Humanities
	Social Science
	Hospitality & Tourism
	Agriculture
	Law

Table A2: Grouped Fields of Occupation

COMMERCE	1290	Corporate managers
	1317	General managers of business services
	2411	Accountants and related accounting occupations, Accounting occupations not elsewhere classified, Auditors and related occupations and Articled clerks with accountant/auditor
	2412	Personnel and careers professionals, Consultants: management/personnel
	2419	Business professionals not elsewhere classified, Consultants
	2441	Economists
	3411	Securities and finance dealers and brokers

	3412	Insurance representatives
	3413	Estate agents
	3419	Finance and sales associate professionals not elsewhere classified
	3421	Trade brokers
	3429	Business services agents and trade brokers not elsewhere classified
	3432	Legal and related business associate professionals, Legal business professions and Other business professions
	3433	Bookkeepers
EDUCATION	1211	Rectors/principals of universities/colleges
	2310	Technikon, teacher training, technical and other colleges, university and other higher education institutions teaching professionals and Other post-secondary education teaching professionals
	2320	Secondary education teaching professionals
	2331	Primary education teaching professionals
	2332	Pre-primary education teaching professionals
	2340	Special education teaching professionals
	2351	Education methods specialists
	3310	Primary education teaching associate professionals
	3320	Pre-primary education teaching associate professionals
	3330	Special education teaching associate professionals
	3340	Other teaching associate professionals
	3391	Teaching associate professionals not elsewhere classified
STEM	2111	Physicists and astronomers
	2112	Meteorologists
	2113	Chemists
	2114	Geologists and geophysicists
	2121	Mathematicians and related professionals, Analysts and methodology research
	2122	Statisticians
	2131	Computer systems designers and analysts
	2132	Computer programmers
	2139	Computing professionals not elsewhere classified
	2142	Civil engineers
	2143	Electrical engineers
	2144	Electronics and telecommunications engineers
	2145	Mechanical engineers
	2146	Chemical engineers
	2147	Mining engineers, Metallurgists and related professionals
	2148	Land surveyors, Cartographers and other surveyors
	2149	Architects, engineers and related professionals not elsewhere classified, Industrial/production engineers, Quantity surveyors, Architects, engineers and related professionals not elsewhere classified
	2159	Physical sciences technologists
	2190	Physical, mathematical and engineering science professionals not elsewhere classified
	2210	Scientist

	2211	Biologists, botanists, zoologists and related professionals
	2212	Biological sciences, Chemical sciences, Medical sciences, Physical sciences and Veterinary sciences
	2213	Agronomists, food scientists and related professionals, Agriculture, forestry and food scientists, Natural sciences technologists
	2221	Medical practitioners, physicians, Medical specialists and Medical occupations not elsewhere classified
	2222	Dentists (general), Dental specialists and Other dental occupations
	2223	Veterinarians
	2224	Pharmacists
	2230	Nursing and midwifery professionals, Nursing services managers and Professional nurses
	3111	Natural science technicians
	3112	Civil engineering technicians, Technicians, engineering, civil, Assistants, technical and civil engineering
	3113	Electrical engineering technicians, Technicians, engineering, electrical, Assistants, technical, electrical engineering
	3114	Electronics and telecommunications engineering technicians, Assistants, technical and electronic engineering
	3115	Mechanical engineering technicians, Technicians, engineering, mechanical, Assistants, technical and mechanical engineering
	3116	Chemical engineering technicians
	3117	Mining and metallurgical technicians
	3118	Draughtspersons
	3119	Physical and engineering science technicians not elsewhere classified, Technicians, physical and engeneering science, Assistants, technical, engineering, not elsewhere classified
	3121	Computer assistants
	3123	Industrial robot controllers
	3142	Ships� deck officers and pilots
	3143	Aircraft pilots and related associate professionals, Air transport supervisors, Aircraft pilots, Navigators and Flight engineers
	3144	Air traffic controllers
	3145	Air traffic safety technicians
HEALTH	3211	Life science technicians, Biological science and Medical science
	3212	Agronomy and forestry technicians, Technicians, agronomy and forestry, Assistants, technical and agriculture
	3220	Optometrist� assistants
	3221	Medical assistants
	3222	Sanitarians
	3223	Dieticians and nutritionists
	3224	Optometrists and opticians
	3225	Dental assistants
	3226	Physiotherapists and related associate professionals, Physiotherapists, Masseurs, Therapists not elsewhere classified, Radiographers, diagnostic and therapeutic, Chiropractors, Podiatrists and Supplementary medical professions not elsewhere cla
	3227	Veterinary assistants
	3228	Pharmaceutical assistants

	3229	Modern health associate professionals (except nursing) not elsewhere classified, Homeopaths, Therapists, speech, Therapists, occupational and Health services professions not elsewhere classified
	3231	Nursing associate professionals, Nurses, senior, student, pupil, Nurses, not elsewhere classified (nursing assistants/aids included under personal care and related workers)
	3232	Midwifery associate professionals
	3434	Statistical, mathematical and related associate professionals
Other	2431	Archivists and curators
	2432	Librarians and related information professionals
	2442	Sociologists, anthropologists and related professionals
	2443	Philosophers, historians and political scientists
	2444	Philologists, translators and interpreters
	2445	Psychologists, Psychometricians and Psycho-technicians
	2446	Social work professionals
	2451	Authors, journalists and other writers, Editors, Reporters, journalists, Writers, poets, playwrights and Other writers, commentators, proofreaders
	3213	Farming and forestry advisers/consultants
	3431	Administrative secretaries and related associate professionals
	3439	Administrative associate professionals not elsewhere classified
	3460	Social work associate professionals
	3461	Social work researcher
	3480	Religious associate professionals
Clerks	4121	Accounting and bookkeeping clerks
	4122	Statistical finance clerks
	4131	Stock clerks
	4132	Production clerks
	4133	Transport clerks
	4141	Library and filing clerks
	4142	Mail carriers and sorting clerks
	4143	Coding, proof-reading and related clerks
	4144	Scribes and related workers
	4190	Other office clerks and clerks not elsewhere classified (except customer services clerks)
	4221	Travel agency and related clerks
	4222	Receptionists and information clerks
Machine Operators	8211	Machine-tool operators
	8212	Cement and other mineral products machine operators
	8221	Pharmaceutical and toiletry products machine operators
	8222	Ammunition and explosive products machine operators
	8223	Metal finishing, plating and coating machine operators
	8229	Chemical products machine operators not elsewhere classified

	8231	Rubber products machine operators
	8232	Plastic products machine operators
	8240	Wood products machine operators
	8251	Printing machine operators
	8252	Bookbinding machine operators
	8253	Paper products machine operators
	8262	Weaving and knitting machine operators
	8263	Sewing-machine operators
	8264	Bleaching, dyeing and cleaning-machine operators
	8269	Textile, fur and leather products machine operators not elsewhere classified
	8271	Meat and fish-processing machine operators
Elementary Occupation	9111	Street food vendors and related workers
	9112	Street vendors, non-food products
	9113	Door-to-door and telephone salespersons
	9120	Shoe cleaning and other elementary street services occupations
	9131	Domestic helpers and cleaners
	9132	Helpers and cleaners in offices, hotels and other establishments
	9133	Hand-launderers and pressers
	9141	Building caretakers
	9142	Vehicle, window and related cleaners
	9151	Messengers, package and luggage porters and deliverers
	9152	Doorkeepers, watchpersons and related workers
	9153	Vending-machine money collectors, meter readers and related workers
	9161	Garbage collectors
	9162	Sweepers and related labourers
	9190	Elementary sales and services occupations not elsewhere classified
	9211	Farmhands and labourers
	9212	Forestry labourers
	9213	Fishery, hunting and trapping labourers
	9311	Mining and quarrying labourers
	9312	Construction and maintenance labourers: roads, dams and similar constructions
	9313	Building construction labourers
	9321	Assembling labourers
	9322	Hand-packers and other manufacturing labourers
	9331	Hand or pedal vehicle drivers

Note: Occupation list and codes are from Statistics South Africa 2001 census

Table A3: Number of observation for each field of study

Field of study	**Frequency**	**Percentage**
Law	1,448	2.63
Agriculture	839	1.52
Commerce	15,932	28.91

Education	6,233	11.31
Humanities & Social Science	3,729	6.77
Health	5,243	9.51
STEM	16,037	29.1
Other	5,657	10.26
Total	55,118	100

Table A4: Description of Variables

Variable	Survey Question
Fields of study	If Degree, Diploma or Certificate: In which field is the respondent's highest post-school qualification?
Highest level of education	What is the highest level of education that... has successfully completed? *Diploma or certificate should have been at least six months* *study duration full time (or equivalent)*
Hours worked	Thinking of each day last week (Monday to Sunday), how many hours did you actually work?
Employment Sector	Is the organisation/ business/ institution/ establishment you work for classified as: 1 = National/Provincial/Local government? 2 = Government controlled business (e.g. Eskom/Telkom)? 3 = A private enterprise? 4 = Non-profit organisation (NGO/CBO)? 5 = A private household? 6 = DON T KNOW
Firm Size	How many employees are there at your place of work?
Highest education qualification	What is the highest level of education that... has successfully completed?
Employment contract	Is the contract/agreement of a............ 1= Limited duration? 2= Permanent nature? 3= Unspecified duration

Note: Survey questions are from the QLFS

Table A5: Sample Characteristics by age group

	Youth	**Non-Youth**	**Total**
field of study			
Commerce	6,142	5,668	11,810
	37.24	**34.42**	**35.83**

Education	1,974	3,323	5,297
	11.97	**20.18**	**16.07**
Health	1,956	2,200	4,156
	11.86	**13.36**	**12.61**
STEM	6,421	5,275	11,696
	38.93	**32.04**	**35.49**
Total	16,493	16,466	32,959
	100	100	100
Gender			
Male	8,098	7,889	15,987
	49.1	**47.91**	**48.51**
Female	8,395	8,577	16,972
	50.9	**52.09**	**51.49**
Total	16,493	16,466	32,959
	100	100	100
Population group			
African/Black	11,499	10,930	22,429
	69.72	**66.38**	**68.05**
Coloured	1,198	1,155	2,353
	7.26	**7.01**	**7.14**
Indian/Asian	872	903	1,775
	5.29	**5.48**	**5.39**
White	2,924	3,478	6,402
	17.73	**21.12**	**19.42**
Total	16,493	16,466	32,959
	100	100	100

Table A6: Tabulation of miss match

Missing Earnings Data	Matching Variable			
	Full Match	Horizontal Mismatch	Vertical mismatch	Total
Commerce				
Missing	372	270	939	**1581**
Available	951	977	4204	6132
Total	1323	1247	5143	7713
STEM				
Missing	623	240	839	**1702**
Available	1983	926	4597	7506
Total	2606	1166	5436	9208