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How well matched are South African workers to their jobs?

A comprehensive analysis of education and skills mismatch

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LABOUR MARKET
INTELLIGENCE PARTNERSHIP

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CONTENTS

LIST OF TABLES

LIST OF ABBREVIATIONS AND ACRONYMS

DHET	Department of Higher Education and Training
GDP	gross domestic product
HSRC	Human Sciences Research Council
ISA	indirect self-assessment
ISCO	International Standard Classification of Occupations
JA	job analysis
LMIP	Labour Market Intelligence Partnership
QLFS	Quarterly Labour Force Survey
RM	realised match
SASAS	South African Social Attitudes Survey
SASCO	South African Standard Classification of Occupations
SR	skills relevance
SU	skills underutilisation
UK	United Kingdom
USA	United States of America

PREFACE

This Human Sciences Research Council (HSRC) working paper is part of the Labour Market Intelligence Partnership (LMIP), a project commissioned by the Department of Higher Education and Training (DHET) and funded through the National Skills Fund. The central objective of the LMIP is to develop 'a credible institutional mechanism'. The challenge for any government is to anticipate the skills that are needed for the current and future economy. This information can be used to plan the size and shape of the post-school education and training system.

In 2013, as part of Theme 1, 'Establishing a foundation for labour market information systems in South Africa', the Education and Skills Development Research Programme piloted a module of 40 questions related to Public Perceptions of Work in the South African Social Attitudes Survey (SASAS). Data was collected from a nationally representative sample of 2 885 respondents that included the employed (30%), unemployed work-seekers (37%) and the economically inactive (33%) in the labour market. The data collected was on public perceptions of the labour market; perceptions of those in employment about quality of employment; and perceptions of those without jobs about prospects of labour market participation and their work-seeking behaviour. Initial analysis of the data was conducted and the report, 'Public Attitudes to Work in South Africa', was published (www.lmip.org.za). The present working paper presents an econometric analysis of the data on public perceptions of work and thus serves as an extension of the research agenda seeking to gain more insight into social attitudes of ordinary South Africans to the labour market.

Specifically, the paper provides an in-depth analysis of skills and qualification mismatch in South Africa, thus adding to the literature and debates on conceptualisation and measurement of these phenomena. It examines the extent of overqualification and underqualification among employed South Africans and further identifies the links to demographic and socio-economic determinants.

1 INTRODUCTION AND RATIONALE FOR THE STUDY

In recent years, matching the skills of the workforce with the needs of the labour market has become increasingly imperative worldwide, perhaps even more so in South Africa where the unemployment rate reaches 27% (StatsSA 2016). The goal of this study is to analyse data collected through the South African Social Attitudes Survey (SASAS) in order to measure job matching and skills development in the South African labour market. In particular, the study examines the extent of overqualification and underqualification among employed South Africans and then identifies the links to demographic and socio-economic determinants.

Skills mismatches affect societies at both the microeconomic and macroeconomic levels. Overeducation often means lower returns on investment in education, and therefore individuals cannot enjoy better wages. Moreover, they might be unhappy and gain very little satisfaction from their work. On the other hand, underqualified employees will be less productive and at risk of losing their jobs. For firms, both overeducation and undereducation in the workforce lower the chances for growth, inhibit productivity and innovation, and might increase the staff-turnover rate. For developed countries, and the United Kingdom (UK) in particular, the increased number of highly educated individuals has often corresponded with high rates of graduate unemployment and mismatches in qualifications.

In developing and middle-income countries, a poorly educated or underskilled workforce tends to compromise economic growth and development. South Africa, in particular, is affected by considerable skills shortages due to its political history and the legacy of restricted opportunities in the labour market. Skills shortages are to be observed in both low- and high-skilled professions in South Africa, and may be absolute (i.e. lack workers with specific skills) or relative (skilled workers exist but do not meet the employment criteria) (Daniels 2007). On the other hand, the presence of undereducation among graduates may suggest that the education system is failing to identify appropriate career paths for graduates (Mncwango 2016). For both developed and developing countries, occupational mismatch suggests labour market inefficiency, which leads to higher unemployment, reduced gross domestic product (GDP) growth and decreased productivity.

Although the concept of occupational mismatch is difficult to define and measure, there are several methods available in the labour market literature. A major distinction lies between the two necessary attributes of performing a job: the education and skills of the worker. Although educational attainment has been used extensively as a way to quantify qualification mismatch, it might not adequately describe an individual's skills that can be further developed by way of work experience and training. Therefore, several definitions and methods of obtaining these measures exist. One popular method is to identify employees as 'overeducated' if their educational qualifications are higher than those required for a particular job. Skills mismatch may be defined as the lack of necessary skills to perform the job or the underutilisation of skills which have been acquired. Often, the extent of over-education varies according to the indicator used and whether it measures education or skills mismatch.

Both educational and skills mismatch need to be considered for South Africa, as both appear to be prevalent (Beukes et al. 2016; Daniels 2007; Mncwango 2016; Reddy et al. 2016). This paper aims to exploit a unique data set in order to expand an earlier analysis of overqualification (Mncwango 2016) where a single measure was explored. The study aims to explore educational and skills mismatch at the microeconomic level by measuring discrepancies between the education or skills possessed by workers with those required by their jobs. It provides the technical framework and formal definitions to add to the recent Labour Market Intelligence Partnership (LMIP) report on skills supply and demand by Reddy et al. (2016).

Educational mismatch

Workers are *overeducated* or overqualified if their formal-education level or formal qualifications are higher than the required education level for the job. The opposite is true for *undereducated* workers.

Skills mismatch

Skill shortage occurs when there is a lack of workers with required skills in the labour market.

Skill underutilisation suggests that a worker's skills are above the skills required for the job.

Skill deficit means that a worker's skills do not meet the requirements for the job.

The remainder of the report is structured as follows. The literature review is discussed in Section 2, while the data, definitions and methods are described in Section 3. Section 4 presents results on the comparison of, and relationship between, several definitions of occupational mismatch, the determinants of overqualification and underqualification as well as skills mismatch, the effect of occupational mismatch on acquiring additional training and reporting increased skill requirements, and, finally the relationship between occupational mismatch and job satisfaction. In the last section (Section 5), we address the limitations of the study and discuss policy implications.

2 LITERATURE REVIEW

2.1 Theoretical framework

The phenomenon of qualification mismatch has been analysed extensively and linked to labour market theories such as the human-capital, career-mobility, signalling-hypothesis, individual-preferences, and job-search frictions (Leuven & Oosterbeek 2011; Quintini 2011b). However, no single theory offers a comprehensive explanation. The *human-capital* theory suggests that qualification mismatches occur only in the short term while firms change their production process in order to fully utilise the individuals' human capital, and could be due to workers' lack of experience or firms' lack of information on the workers' skills. The *job-competition* theory assumes that qualifications are a proxy for training costs, and, therefore, that the most qualified require less training (Berg 1970). This forces individuals to acquire more qualifications in order to compete with others, even though they might not get a job that fully utilises their qualifications. According to the job-competition theory, qualification mismatch is persistent. *Signalling* theory (Spence 1973) implies that, when the average level of education in the labour market rises due to increased investment in education by lower-ability individuals, firms will raise the required education level in order to secure workers with a certain ability level. Finally, with the *assignment* model, workers should be assigned jobs according to their skills so that the most skilled perform the most demanding jobs, and vice versa. Any occupational mismatch results from discrepancies between the number of skilled workers and highly demanding jobs. Studies that have tried to empirically test which theory is most relevant tend to find that assignment theory performs the best in terms of identifying educational mismatch and its effects on earnings (Allen & De Weert 2007; Allen & Van der Velden 2001; Duncan & Hoffman 1981; Hartog & Oosterbeek 1988; McGuinness 2006). However, many studies fail to identify one dominant theory and conclude that that there is a great overlap among them. The analysis in this paper provides an excellent starting point for future research on identifying the theory that best fits the labour market in South Africa.

2.2 Measuring educational mismatch

Several educational-mismatch indicators exist in the literature and can be divided into objective and *subjective* measures. Objective approaches are further disaggregated into *normative/job analysis (JA)* and *statistical/realised matches (RMs)*, while the subjective measures can be *direct* and *indirect self-declared* (Flisi et al. 2014; Quintini 2011b). Despite the expected differences, few studies have attempted to estimate and compare different measures from the same data set in order to understand the extent of occupational mismatch (Allen & Van der Velden 2001; Flisi et al. 2014; Green & McIntosh 2007; Verhaest & Omey 2006a, 2006b). Since all of the measures come with their own particular trade-offs, each is now described briefly below.

The *normative* approach involves the evaluation of jobs by experts in order to identify the educational level required for a job and to organise jobs into occupational classifications. Workers are then categorised as matched, overeducated or undereducated according to their educational attainment. The advantage of this method is that expert job analysts decide on the education level required for a job. On the other hand, it assumes that all jobs within the same classification group require the same level of education, which is not always true. As the list of occupations is costly to compile, it also has the disadvantage of not being updated frequently enough. In terms of the South African context, the South African Standard Classification of Occupations

(SASCO) is an example of a job-classification framework that may be used to obtain the normative measure (Beukes et al. 2016), as it provides a list of occupations at national level and is compatible with the International Standard Classification of Occupations (ISCO). Equivalent job-classification systems such as the Standard Occupational Classification System in the United Kingdom (UK), the Dictionary of Occupational Titles in the United States of America (USA), or others, have been used for obtaining objective measures of overeducation in numerous studies such as those by Battu et al. (2000), Chevalier (2003), Kiker et al. (1997) and Verhaest and Omey (2006a).

With the *statistical* method, the distribution of the education level of individuals within each occupation code is used to calculate the educational-mismatch measure. The worker's education level is then compared with the mean or the mode of the education level at their given occupation group (at the one- or two-digit level of SASCO), and, if it deviates by more than a certain value, the worker is classified as overeducated (or undereducated) (Bauer 2002; De Oliveira et al. 2000; Kiker et al. 1997; Verdugo & Verdugo 1989). The statistical approach has the advantage of small data requirements, but it is sensitive to cohort effects, to the choice of the unit of deviation, and to the level of aggregation (Flisi et al. 2014).

Finally, *self-declared* or *self-assessment* methods are based on subjective questions about workers' perceptions of the required education level for their jobs. The direct self-assessment approach uses questions that assess directly the match or relevance of one's job to one's level of education. Indirect questions ask workers about the education requirements for their jobs. Obviously, these methods depend to a great extent on the respondents' self-reported perceptions and are subject to bias (Flisi et al. 2014; Hartog 2000). The most common is upward bias, as employees often tend to overstate the required education level for their jobs. Nevertheless, subjective measures of job matching are easily obtainable and widely used in the literature (Battu et al. 2000; Chevalier 2003; Duncan & Hoffman 1981; Hartog & Oosterbeek 1988; Sloane et al. 1999; Verhaest & Omey 2006b).

2.3 Measuring skills mismatch

A closely related, yet distinct, concept which has received substantial attention in the literature is that of *skills* mismatches in the labour market. Skill imbalances may be due to skills shortages, skills deficit or the underutilisation of skills. Skills shortages occur when there are not enough skilled individuals in the labour market to fill the available positions. Related to this, a skills deficit occurs when workers lack the necessary skills to perform a job. Skills underutilisation, on the other hand, is present when workers possess skills that surpass those required for the job. Previous studies have shown that skills mismatch should not be ignored, since it is often the case that occupational mismatch can be explained through skills imbalances instead of educational mismatch. Moreover, it has been found that, even among well-matched workers, there is evidence of significant skills underutilisation or skills deficit (Allen & Van der Velden 2001). A generally weak correlation between qualification and skills mismatch in the empirical literature suggests that both measures should be investigated in order to understand imperfections in education, qualifications, and skills development in the labour market.

Measuring skills mismatch has increasingly been the focus of several studies, as the acquired qualifications often do not represent the skills that an individual possesses or which are required to perform a job; hence a number of studies have focused on skills mismatch despite data limitations for measuring skills (Allen & Van der Velden 2001; Green & McIntosh 2007; Mavromaras et al. 2007). Similar to the approaches which measure overeducation, a number of different methods exist for identifying the overutilisation and underutilisation of skills. The objective methods (normative and statistical) have limited application, since it is often not possible to assess certain types of skills (Perry et al. 2014). Objective methods therefore typically rely on assessing skills in literacy, numeracy or problem-solving (Allen et al. 2013; Desjardin & Rubenson 2011). On the other hand, self-assessment measures are easier to implement through questions which ask workers to evaluate the utilisation of their skills and expertise at work, thereby measuring their satisfaction with the extent to which they feel that their skills are being used or their need for further training in order to meet the requirements of the job (Allen & Van der Velden 2001; Green & McIntosh 2007; Halaby 1994; Mavromaras et al. 2007; Vieira 2005). Skill mismatch can be defined in terms of skill underutilisation (overskilling), skill deficit or skill irrelevance. An important observation in previous studies has been that there is often a weak link between skills mismatch and education mismatch, which suggests significant skill diversity among workers with the same qualifications.

In addition to the above measures, a number of *mixed* approaches exist in the literature that combine both education-mismatch and skills-imbalance indicators to identify genuine and perceived overqualification (Chevalier 2003; Green & Zhu 2010). However, these measures are beyond the scope of this paper.

2.4 Determinants and consequences of occupational mismatch

Many studies examine the determinants of occupational mismatch. However, the majority of the studies explore only educational mismatch and not skills mismatch. In addition, a great number of them focus specifically on overeducation (Green & McIntosh 2007) among university graduates. A few find weak associations between overeducation and individual characteristics such as gender, age or race. There is no clear direction of the association between gender and overeducation, with some studies showing higher prevalence for women but others not. Green and McIntosh (2007) find that, apart from age, which is negatively associated with overqualification, all other significant factors are job- or degree-specific (part- or full-time job, size of the firm, type of degree and university). According to Dolton and Silles (2008), employees in part-time jobs have been found more likely to be overqualified. Quintini (2011a, 2011b) also discusses how ethnicity and migration status seem to be important determinants of overeducation in previous studies.

Green and McIntosh (2007) also explore the determinants of skills mismatch and find that non-prime-age workers and those in unstable jobs are more likely to be overskilled. However, one of their findings is that being a graduate and overqualified does not necessarily translate into overskilling. Some studies investigate both qualification and skills mismatch and attempt to interpret the relationship between the two (Allen & De Weert 2007; Allen & Van der Velden 2001), and most of them show that, although the two mismatch types might be related, one does not necessary imply the other.

An important aspect of occupational mismatch is the opportunity of participating in additional training and whether training reduces the gap between possessed and required skill. Previous studies in the literature have attempted to determine whether education and on-the-job training may be substitutes for, or complements of, each other (Alba-Ramirez 1993; Groot 1993; Van Smoorenburg & Van der Velden 2000). Sloane (2003) suggests that, if they are substitutes, overeducated workers need less training than well-matched workers in order to perform their job, because their education can replace training. If the second hypothesis is true, then overeducated individuals who also receive training are at a greater advantage than the undereducated and are more likely to be promoted. While additional training would be less likely for overeducated workers because their education provides them with different skills, undereducated individuals might desire, and benefit from, additional training in order to increase their experience or knowledge and subsequently become a better match for the job. Van Smoorenburg and Van der Velden (2000) show that overeducated workers are less likely to participate in training than well-matched workers. The evidence is mixed, however, and another study found that underqualified workers are the least likely to participate in training (Groot 1993). In general, findings in the literature may vary depending on the study, but seem to suggest that additional training is one of the remedies for occupational mismatch.

The relationship between occupational mismatch and job satisfaction has been previously addressed in a number of studies such as those of Allen and De Weert (2007), Allen and Van der Velden (2001), Battu et al. (2000), Chevalier (2003), Green and Zhu (2010), McGuinness and Sloane (2011), Verhaest and Omey (2006b) and Vieira (2005). In general, overeducated workers are found to be less satisfied with their jobs than well-matched workers, even among those with the same qualifications or in the same job. However, the effect of educational mismatch becomes non-significant when controlling for skills mismatch and/or other job characteristics.

2.5 Findings from South Africa

Only a handful of studies from South Africa have examined the prevalence of, and factors associated with, occupational mismatch, despite the fact that high unemployment is accompanied by both a shortage of key skills and a relatively high level of overqualification (Daniels 2007; Mncwango 2016). In a recent Labour Market Intelligence Partnership (LMIP) report (Mncwango 2016) based on the South African Social Attitudes Survey (SASAS), approximately 30% of employed individuals were found to be overqualified when using the self-declared measure. This study also showed that female, black Africans and workers between 25 and 34 years are more likely to be overqualified, although no confidence intervals or standard errors are reported. Further findings such as a high prevalence of overeducation among workers with primary schooling suggest there might an upward bias in this subjective measure. Beukes et al. (2016) discuss two definitions of underemployment: the 'time-related' measure and 'inadequate-employment situations' using the Quarterly Labour Force Survey (QLFS). The latter definition is translated into skills underutilisation or overqualification. The authors use two objective methods, the normative approach and the statistical approach, to measure overqualification and find that overqualification varied from 15.7 to 27.9% (normative method) and from 6 to 15% (statistical method) in the 2008 to 2014 period. They also find that the greatest proportion of overeducated persons are black Africans, as well as female workers and formal urban dwellers. However, the prevalence of overeducation within each demographic group is not discussed in detail.

Indeed, it is evident that occupational mismatch has received insufficient attention in South Africa, despite the need for measuring it and addressing it with appropriate policy interventions. Reddy et al. (2016) show that less than half of people working in professions that require high qualifications (managers, senior officials, technicians and professionals) have a tertiary education, a fact that makes them seriously underqualified. Moreover, nearly half of higher education graduates work in the community-, social- and personal-services sectors, while many science and engineering graduates choose to work in the financial sector.

Even less researched are the many alternative definitions of occupational mismatch, its determinants, and its consequences for job satisfaction, additional training and skills development. In this paper, we try to address and understand occupational mismatch in order to assess whether its extent and impact constitute a real problem in South Africa. We also discuss policy implications.

3 DATA AND METHODOLOGY

3.1 Data

The analysis in this paper is based on the 2013 edition of the South African Social Attitudes Survey (SASAS). The survey is a nationally representative, repeated cross-sectional survey and has been conducted annually by the Human Sciences Research Council (HSRC) since 2003. The SASAS aims to capture public attitudes, and changes in public attitudes, regarding cultural, social, political and economic values in South Africa. The study uses a representative sample under the sampling frame designed by the HSRC in 2002. The Master Sample contains 1 000 primary sampling units based on the 2001 population census estimates (Roberts, Wa Kivilu & Davids 2010). Face-to-face interviews were used to collect information and a total of 2 885 South Africans aged 16 years and older participated in the study.

Although the questionnaire includes a number of fixed questions every year, such as demographic and other behavioural variables, there is also a module on specific themes that differs from year to year. In 2013, the particular module focused on questions about attitudes to the labour market initiated by the Labour Market Intelligence Partnership (LMIP). The module included 41 questions on work values, the perceived role of education in positive labour market outcomes, perceived barriers to employment, and subjective evaluations of work and job-search attitudes and behaviours. After excluding unemployed and economically inactive individuals, the data set consists of 844 employed respondents (16 years and older). Tables A1 to A9 (Appendix A) describe the relevant variables used in the analysis below.

3.2 Qualification-mismatch measures

In order to analyse job mismatches, the analysis makes use of a range of different measures. We compute a normative measure, the indirect self-assessment measure (ISA), and four measures with the statistical approach – two using the mean and two using the mode. We also obtain two skill-utilisation measures from subjective questions in the SASAS questionnaire.

The objective measure using the *job analysis (JA)* method employs the South African Standard Classification of Occupations (SASCO) 2003[1] list

1 Although a more recent SASCO list exists, the 2003 version was used in the SASAS to classify occupations and is therefore utilised for this analysis.

Table 1: Occupation groups and skill levels

Major occupation group	Education level	Skill level
1. Legislators, senior officials and managers	Tertiary	4
2. Professionals	Tertiary	4
3. Technicians and associate professionals	Diploma/certificate	3
4. Clerks	Secondary or equivalent	2
5. Service workers and shop and market sales workers	Secondary or equivalent	2
6. Skilled agricultural and fishery workers	Secondary or equivalent	2
7. Craft and related trades workers	Secondary or equivalent	2
8. Plant and machine operators and assemblers	Secondary or equivalent	2
9. Elementary occupations	Primary or less	1
0. Armed forces, occupations unspecified and not elsewhere classified, and not economically active persons	Various	1+2+3+4

which classifies jobs into ten major occupational groups (Table 1). According to the SASCO document, 'a skill is defined as the ability to carry out the duties and tasks of a specific job'. The skill level represents the range and complexity of the set of tasks or duties required for a job and is measured by means of formal education and experience. According to SASCO 2003, there are four major skill levels. The first skill level is equivalent to primary education, but might also include workers without any formal education; therefore, it might be seen as conceptually combining skills and education. The second skill level represents secondary education, which starts at the age of 13 or 14 and lasts for five years, as well as some apprenticeship or on-the-job training. SASCO defines the third skill level as education that starts at the age of 17 or 18, lasts between one and four years, and leads to a degree that is not equivalent to a university degree (e.g. a diploma or certificate). Finally, the fourth skill level corresponds to education that begins at the age of 18 or 19, lasts for three or more years, and results in a university degree (undergraduate or postgraduate). Note that, for Occupation Groups 0 and 1, SASCO 2003 did not assign a skill level; hence the relevant information was extracted from the job description at the two-digit level (if appropriate) or from SASCO 2012.

The second objective method is the *statistical approach*, which uses the mean or the mode of the education level or years of schooling for each of the worker occupation groups based on the SASCO. Educational mismatch is then defined as the deviation of an individual's education from the mean or mode in the specific occupation group. When using the mean, workers with educational attainment (in terms of years of schooling) greater than one standard deviation from the mean are defined as overeducated, and vice versa. Workers with education within one standard deviation from the mean education of their occupation group are educationally matched. The method is applied to the one- and two-digit levels of occupation codes. Similarly for the mode, a worker is classified as overeducated when his or her educational attainment is greater than the modal value within the specific occupational group, undereducated if his or her education is below the mode, and matched if it is equal to the mode. In this case, we use the education-attainment variable rather than the years of schooling, again at the one- and two-digit levels of occupation codes.

The only subjective overqualification measure available in the SASAS is the *indirect self-assessment (ISA)* measure using the following question from the SASAS (adapted from: Dolton & Silles 2008; Dolton & Vignoles 2000):

> *What do you think should be the minimum level of education required to perform your job?*

The response categories for this question are: (1) none – no schooling required; (2) primary education; (3) some secondary education; (4) matric/Grade 12 certificate; (5) certificate or diploma; (6) university degree; and (7) university degree with a higher qualification (see Table A4). The answers are recoded into five categories and then compared with the individuals' education level in order to obtain the ISA measure. A worker is classified as overeducated if the required education is less than their actual education, matched if it is equal, and undereducated if it is higher.

3.3 Skills-mismatch measures

In addition to the education-mismatch measures, we create two skills-mismatch measures based on subjective questions asked in the SASAS 2013. The first question is a statement about utilisation of skills:

> *The work that I do makes full use of my knowledge and skills.*

The respondent has to answer one of the following: 'strongly agree' (1); 'agree' (2); 'neither agree nor disagree' (3); 'disagree' (4); 'strongly disagree' (5); or 'can't choose' (8). Allen and Van der Velden (2001) define the 'skill underutilisation' (SU) variable as the extent to which an individual agrees with the above statement: strong if one answers 4 or 5 and none if one chooses answers 1 to 3. Similarly, we create a *skills-relevance (SR)* variable by using the question, *To what extent is your expertise relevant to what you do in your job every day?*

with potential answers being: 'completely relevant' (1); 'to a great extent' (2); 'to some extent' (3); 'not at all relevant' (4); 'have not received any training or qualification' (5); or 'don't know' (8)'. A new variable is created to represent skill relevance to job, with 'strong' assigned to answers 1 and 2 and 'weak' to answers 3 to 5.

4 ANALYSIS

4.1 Sample descriptives

A total of 844 employed individuals are included in the analysis of education and skills mismatch. Sample characteristics are shown in Appendix A, as well as descriptives for all relevant variables and information about missing values. We see that men and women are almost equally represented in the sample, with 51% of the workers being men. Black Africans comprise the majority of the sample (53%), but are underrepresented among workers when compared with their share of 80% percent in the complete South African Social Attitudes Survey (SASAS) sample (Mncwango 2016). All other population groups are over-represented (19% Coloured, 10% Indian and 18% white). Approximately 11% of the sample is 16 to 24 years old and 13% are above the age of 55, while the remaining 76% are in the prime working age (25–54 years). Only 2% of the workers have not had any schooling and 34% have completed matric or equivalent education level (NTC 3). It is interesting that individuals with tertiary education are over-represented among employed respondents (24% versus 12% in the whole sample – see Mncwango 2016). Eighty per cent of the workers live in formal or informal urban areas.

More than 20% of the employed respondents work in elementary occupations such as domestic helpers, informal workers, or mining and construction labourers (Table A3). Another 15% are high-skilled professionals (mathematical, engineering, or life sciences and health), and 12% work as service, shop and market sales workers. The shares of the remaining occupational groups are below 10%: 7% work as legislators, senior officials and managers, 8% as technicians, and 8% as clerks, with only 2% working as skilled agricultural and fishery workers and only 6% working as machinery or plant operators. According to SASCO 2003, 22% of the workers belong to the Skill Level 1 group, 48% to Skill Level 2, 8% to Skill Level 3 and 22% to Skill Level 4 (Table A4).

4.2 Occupational-mismatch measures

The following tables show the education- and skills-mismatch prevalence in the sample according to the measures discussed above. We see that the

Table 2: Occupational mismatch in the sample (row percentages in parentheses)

Educational mismatch			
	Matched	Underqualified	Overqualified
Objective			
Job analysis (JA)	377 (49)	210 (27)	189 (24)
MODE2	375 (48)	239 (31)	162 (21)
MEAN2	596 (72)	111 (14)	118 (14)
Subjective			
Indirect self-assessment (ISA)	388 (50)	152 (20)	236 (30)
Skills mismatch			
		Strong	None
Skill underutilisation (SU)		151 (19)	625 (81)
		Weak	Strong
Skills relevance (SR)		348 (45)	428 (55)

Source: SASAS 2013. Data are unweighted.

statistical approach using the mean produces the highest percentage of matched individuals (72%), while the remaining measures suggest that, for approximately half of the sample, their education matched the required education for the job. However, there are differences in the prevalence of the overeducation and undereducation by measure, with the subjective measure (indirect self-assessment [ISA]) giving the highest overeducation rate and the MEAN2 giving the lowest. This is consistent with the hypothesis that subjective measures tend to overestimate overeducation (Hartog 2000; Verhaest & Omey 2006b). On the other hand, undereducation appears to be highest when using the MODE2 measure and lowest with the MEAN2 measure, which shows that the choice of a specific method within the same approach also influences the estimated prevalence of occupational mismatch.

Several reasons have been suggested in the literature to explain the variation among qualification-mismatch measures or the reasons for its overestimation or underestimation by certain measures (Hartog 2000; Verhaest & Omey 2006b). Apart from measurement error resulting from data collection, particular measures suffer from certain disadvantages. Objective measures collapse a wide range of occupations into specific categories which are assigned the same required education, while this might not in fact be the case. Subjective measures, on the other hand, may be biased by poorly informed individuals who are not able to evaluate their job requirements accurately or by job experts who may lack complete information about a job specification.

In examining skill imbalances in the SASAS 2013 data, we see that 19% of all workers in the sample report strong underutilisation of skills (overskilling), and the respective percentage in the population is 20% (weighted). Skill relevance is also an important aspect of skill imbalances to consider, as individuals often choose jobs that are outside their field of expertise (Reddy et al. 2016). Approximately 45% of the workers in the sample experience weak skill relevance (with 47% being the respective weighted percentage), a percentage much higher than the skill underutilisation percentage. Moreover, low skill relevance appears to be higher among overqualified workers than among underqualified workers (56% versus 36%; p-value = 0.005).

4.3 Correlation and correspondence between measures

Given the large differences both between and across measures of qualification matching, Table A10 presents the proportion of workers that are classified the same with the respective measures. For example, a value of 0.62 correspondence between the JA and MODE2 measure means that the classification of 62% of the workers is the same with both measures (Table A10). In other words, if one respondent is classified as overeducated with the JA measure, he or she is also classified as overeducated using the MODE2 measure. The high proportion of correspondence between the two realised matching indicators may be a result of using the distribution of education within occupation group. The subjective indicator (ISA) has the lowest correspondence with any other measure, suggesting that it might be more biased than the other measures. Interestingly, in investigating the particulars of the correspondence between measures, we find that, while all workers are overeducated according to at least one measure, only 4% of them are overeducated with regard to every measure (similar findings are recorded by Verhaest & Omey 2006a). Similarly 15% of workers are classified as well matched and 4% as undereducated with all measures.

While few studies in the literature have attempted to measure the correlation between measures (Battu et al. 2000; Verhaest & Omey 2006a), they have found that occupational-mismatch measures tend to be only weakly correlated. Similarly, we show that there is a level of correlation between them, but that this is not strong (Table A11): the highest correlation is between the normative measure and the statistical measure using the mode (0.34). The second largest correlation coefficient (absolute value of 0.32) is observed between the two skills-assessment measures, with the negative sign due to the reverse coding of the skills underutilisation variable. Interestingly, very low correlation coefficients appear and some are even negative. For example, the skills relevance and the ISA measure are negatively associated (Spearman rank correlation coefficient of –0.19). This suggests that educational and skills mismatch may be independent of each other. Further investigation is therefore needed to identify the reasons for this and to determine what this might mean for skills development and policymaking.

The remaining analysis focuses on the objective JA measure as the preferred educational-mismatch measure, the reason being that it appears to be superior to the realised match (RM) measure because it relies on information obtained by job experts. We also aim to further investigate the skill-underutilisation indicator and juxtapose it with the JA measure in order to identify conceptual differences. We choose the skill-underutilisation indicator as opposed to the skill-relevance measure, as it is the one most often used in the literature. However, we recognise the need to explore more occupational-mismatch indicators in order to conceptualise labour market imbalances specific to South Africa.

4.4 Overeducation and skills underutilisation

The following analysis focuses on the JA measure as well as the skills-mismatch indicators as defined by SU. Population weights are used in order to obtain population statistics and account for unequal selection probability or non-response. Interestingly, the prevalence of overskilling does not differ significantly among the three educational-mismatch groups, which suggests that educational mismatches do not necessarily imply skill mismatches (Table B1).

We then obtain population statistics for the JA indicator by way of several demographic and socio-economic factors (Table B2). It is evident that workers with matched education account for less than half of all employed individuals (46%), while there is no significant difference between overall rates of overeducation and undereducation. Pearson's X^2 test is used to test whether educational mismatch and any of the factors below are significantly associated. Women tend to be more overeducated (33% versus 23% of men), but the difference is significant only at the 10% level of significance (p-value = 0.071). Race is found to be associated with educational mismatch, with Coloured respondents being the most matched (54%) and whites the least (41%). Indians are the least likely to be overqualified for a job (7%), while whites are the most likely to be overeducated (39%). Exploring occupational mismatch by age groups shows that adults from 35 to 44 years of age are seemingly the most matched in respect of jobs, with adults 55 years or older being the least matched. In addition, overqualification tends to be higher among those from 25 to 44 years of age, but also among the oldest workers. A significant association appears between province and qualification mismatch: only 27% of the workers living in the Eastern Cape are well matched, while approximately 61% of them are well matched in the Northern Cape. Dramatic differences exist in the percentages of underqualification (36% in Mpumalanga versus 12.5% in the Free State) as well as in the overqualification rates (42% in the Eastern Cape versus 19% in Mpumalanga). Respondents appear to be less matched in rural areas, where they are also more likely to be undereducated (Table B2).

As expected, we see that overeducation is non-existent at the lowest education levels (no schooling and primary), and reaches 39% for workers with tertiary education, as shown in Table 3. Although underqualification is higher among workers with basic education, it persists for workers with matric and tertiary education.

Table 4 presents the qualification mismatch among the major occupational groups in the South African Standard Classification of Occupations (SASCO). Interestingly, the percentage of underqualified individuals is highest (78%) among Occupation Group 1, which consists of legislators, senior officials and managers. The majority of skilled agricultural and fishery workers also appear to be underqualified (73%). The groups with the highest prevalence of well-matched workers are Group 8 (plant/machine operators and assemblers) with 81%, Group 5 (service and shop sales workers) with 75%, and Group 4 (clerks) with 71%. Approximately 75% of workers in elementary occupations are classified as overqualified, suggesting that individuals may be choosing these occupations out of necessity and despite having more qualifications than required for the job. Technicians and associated professionals constitute the second-most overqualified profession. The lower rates of overqualification are evident in occupational groups that require high levels of skills or qualifications, such as professionals, legislators and skilled workers (Green & McIntosh 2007).

The prevalence of skill underutilisation or overskilling reaches 20% in the population of South African workers, with women, black Africans, never-married individuals, and respondents who live in urban areas being more likely to be overskilled (Table B3). The fact that skill underutilisation is higher among workers with no schooling than workers with higher education supports the theory that qualifications might not capture effectively the skills required to perform a job and that those with lower education are consigned to the lower-skill jobs (Table 5). It is interesting to observe a clear negative relationship between overskilling and education level, perhaps suggesting that better educated workers can obtain jobs that better suit their skills. Alternatively, higher education might improve someone's chances to better utilise their skills even if they are overqualified for a job (24% of overqualified workers with secondary education are overskilled versus 4% of overqualified workers with some secondary education).

Several interesting findings emerge from closely examining both educational- and skills-mismatch rates. Firstly, we see that overqualification does not translate to overskilling, although it might mean this for some professions. Undereducation is as high as

Table 3: Qualification mismatch (JA) by education level (row percentages)

Variable	Matched	Underqualified	Overqualified
No schooling	50.5 (24.5, 76.1)	49.5 (23.9, 75.5)	0
Primary	38.6 (26.9, 50.5)	61.4 (49.5, 73.1)	0
Some secondary	52.8 (43.9, 61.9)	15 (9.2, 23.3)	32.2 (24.2, 41.2)
Matric	50 (41, 58.5)	28.6 (21.2, 37.3)	21.4 (15.1, 30.1)
Tertiary	39.2 (29, 47.6)	22.3 (14, 32.1)	38.5 (31.6, 50)
Total	**46.3 (41.2, 50.7)**	**27.3 (23, 31.8)**	**26.4 (22.8, 31.3)**

Source: SASAS 2013. Data are weighted using populations weights. X^2 test statistic = 7.3, p-value < 0.001. Confidence intervals in parentheses.

Table 4: Qualification mismatch (JA) by SASCO occupation group (row percentages)

Occupation group	Matched	Underqualified	Overqualified
1. Legislators, senior officials and managers	21.9 (11.7, 37.3)	78.1 (62.7, 88.3)	0
2. Professionals	34.9 (23.5, 48.4)	60.6 (46.4, 73)	4.5 (13, 42.1)
3. Technicians and associate professionals	24.8 (13, 42.1)	47.3 (31, 64.2)	27.9 (15.2, 45.5)
4. Clerks	71.4 (52.1, 85.2)	10.6 (3.1, 30.3)	18 (8.2, 35)
5. Service workers and shop and market sales workers	75.4 (64.2, 83.9)	6.6 (2.9, 14.3)	18 (10.8, 28.5)
6. Skilled agricultural and fishery workers	25.3 (9.7, 51.5)	73.4 (47.5, 89.3)	1.3 (0.2, 9.4)
7. Craft and related trades workers	69 (52.4, 81.8)	21.6 (10.6, 39.1)	9.4 (4.5, 18.4)
8. Plant and machine operators and assemblers	80.9 (64.2, 90.9)	12.2 (4.7, 28.2)	6.8 (2.1, 20.3)
9. Elementary occupations	25.3 (17.9, 34.6)	0	74.7 (65.4, 82.1)
0. Armed forces, unspecified or unclassified	60.9 (48.4, 72)	8.9 (4.4, 17.3)	30.2 (20.3, 42.3)

Source: SASAS 2013. Data are weighted using populations weights. X^2 test statistic = 18.4, p-value < 0.001. Confidence intervals in parentheses.

Table 5: Skill-underutilisation measure by education level (percentage)

Education level	Strong skill underutilisation
No schooling	43.8 (19.1, 72.1)
Primary	39.1 (26.8, 52.9)
Some secondary	26.9 (19, 36.6)
Matric	16.9 (10.8, 25.4)
Tertiary	5.3 (2.5, 10.8)

Source: SASAS 2013. Data are weighted using populations weights. X^2 test statistic = 8.9, p-value < 0.001. Confidence intervals in parentheses.

Table 6: Skills underutilisation by occupation group (percentages)

Occupation group	Strong skill underutilisation
1. Legislators, senior officials and managers	14 (5.2, 32.7)
2. Professionals	4.6 (1.3, 15.3)
3. Technicians and associate professionals	8.8 (3.3, 21.6)
4. Clerks	27.5 (10.5, 54.9)
5. Service workers, shop and market sales workers	26.3 (15.7, 40.7)
6. Skilled agricultural and fishery workers	51.1 (26.8, 74.9)
7. Craft and related trades workers	11.8 (4.6, 27)
8. Plant and machine operators and assemblers	10.3 (2.7, 32.6)
9. Elementary occupations	35.4 (25.7, 46.5)
0. Armed forces, unspecified and not elsewhere classified	17.3 (10.3, 27.7)

Source: SASAS 2013. Data are weighted using populations weights. X^2 test statistic = 3.8, p-value < 0.001. Confidence intervals in parentheses.

Table 7: Marginal effects for multinomial logistic regression of qualification mismatch

Variable	Matched	Underqualified	Overqualified
Female	–0.000 (0.048)	–0.050 (0.045)	0.051 (0.044)
Coloured	0.036 (0.074)	–0.067 (0.060)	0.031 (0.068)
Indian	0.138 (0.094)	0.013 (0.090)	–0.150** (0.046)
White	0.020 (0.072)	–0.112 (0.058)	0.092 (0.066)
25–34 years	0.034 (0.086)	–0.085 (0.083)	0.052 (0.074)
35–44 years	0.028 (0.090)	–0.086 (0.091)	0.057 (0.078)
45–54 years	–0.006 (0.099)	0.011 (0.099)	–0.005 (0.083)
55+ years	–0.052 (0.110)	0.017 (0.113)	0.035 (0.090)
Previously married	–0.004 (0.075)	0.018 (0.075)	–0.014 (0.069)
Never married	0.058 (0.060)	–0.068 (0.059)	0.010 (0.053)
Rural	–0.060 (0.064)	0.063 (0.063)	–0.002 (0.062)
Matric or equivalent	–0.020 (0.058)	–0.002 (0.052)	0.022 (0.050)
Tertiary	–0.107 (0.072)	–0.067 (0.061)	0.175* (0.070)
Strong overskilling	–0.012 (0.062)	–0.038 (0.051)	0.049 (0.056)
Part-time job	–0.059 (0.055)	–0.074 (0.048)	0.133* (0.053)
Observations	783		

Source: SASAS 2013. Data are weighted using populations weights. Marginal effects; standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.
Also controlling for province. The reference categories are: male, black African, 16–24 years old, currently married, urban area, secondary or less, no overskilling, full-time job.

73% for skilled agricultural and fishery workers, but overskilling is the highest among this occupational group. However, the numbers are too small to further explore overskilling by educational level and occupational group (there are only 19 workers in Group 6). Reported skill underutilisation in Group 9 is relatively high (35%), but it is lower than the measured overeducation rate for this group, which is 75%. Breaking down the overskilling by educational-mismatch category in this group shows that education indeed plays a role, as workers who are overeducated report less overskilling than those matched in elementary occupations (33% versus 42%).

4.5 Determinants of occupational mismatch

In the analysis that follows we examine whether any individual characteristics are associated with occupational mismatch as defined by the normative approach (JA). Firstly, we use multinomial logistic regression to link educational mismatch with the following explanatory variables: age, gender, race, education level and marital status; area of residence, province and job type (full or part time)[2]. We also include the skill-underutilisation variable. Results are somewhat consistent with previous findings in the literature and show that educational mismatch is often not correlated with individual characteristics such as gender, race, age or marital status. There is evidence that Indian workers have a significantly lower likelihood of being overqualified, while those with tertiary education or with a part-time job are more likely to be overqualified. Overskilled workers are less likely to be well matched and underqualified and more likely to be overqualified, but the coefficient is not significant.

Next, we model the odds of being overskilled by fitting a logistic regression model. The same socio-economic covariates are included in the model in order to identify potential factors influencing skill underutilisation. Two different models are fitted: Model 1 has the same explanatory variables as for qualification mismatch, and Model 2 incorporates occupational group in addition to the other variables. In Model 1, women have higher odds of reporting skill underutilisation, as do black Africans, older workers, those living in rural areas, and overqualified workers, but the coefficients are not significant. On the other hand, the coefficient for never-married workers is positive and significant in both Model 1 and 2, showing that never-married individuals have higher odds of being overskilled than married individuals. Higher-educated workers are less likely to be overskilled after controlling for demographic and social factors, but the relationship becomes non-significant after adding occupational group in the regression.

Finally, the two analyses show that educational mismatch and skills mismatch are not significantly associated and that one does not imply the other. Although overqualified workers seem to have higher odds of being overskilled than well-matched workers (non-significant coefficient), the relationship is reversed when controlling for occupational group. These results suggest that occupation group is indeed important in explaining skills mismatch. Unfortunately, there is no information about field of study or vocational training in SASAS 2013 so as to further investigate the reasons for this (Green & McIntosh 2007).

4.6 Additional training and increased skill requirements

As outlined earlier in the report, a key interest is whether levels of overeducation and overskilling are associated with additional training and skills development and perceptions about the value of additional training. The following question in the 2013 SASAS asks whether an employed individual has received any additional training:

> *Over the past 12 months, have you had any training to improve your job skills (either at the workplace or somewhere else)?*

Forty percent of the workers in the sample reported that they had received training to improve their skills (Table A7). Another question potentially related to occupational mismatch is on workers' perceptions about the skill requirements evolution in their job. More specifically:

> *Since you began working on your current job, have the overall skill requirements of the position: increased, stayed the same or decreased?*

2 Personal income is included in additional regression presented in the Appendix. However, due to its number of missing values (179), it is excluded from the final regression presented in the main analysis. Zero frequencies for overqualified professionals and underqualified workers in elementary occupations also cause the multinomial regression of qualification mismatch to fail, but occupational group is controlled for in the remaining outcome regressions.

Table 8: Logistic regression of skills-underutilisation measure

Variable	Skill underutilisation Model 1 OR (s.e.)	Model 2 OR (s.e.)
Male	1	1
Female	1.733 (0.530)	1.505 (0.444)
Black African	1	1
Coloured	0.944 (0.516)	1.013 (0.518)
Indian	0.547 (0.292)	0.627 (0.417)
White	0.609 (0.312)	0.688 (0.340)
16–24 years	1	1
25–34 years	1.603 (0.845)	1.263 (0.640)
35–44 years	1.785 (1.038)	1.484 (0.832)
45–54 years	1.243 (0.813)	0.867 (0.559)
55+ years	1.457 (0.970)	0.991 (0.686)
Married	1	1
Previously married	1.154 (0.512)	1.119 (0.494)
Never married	2.221^{*} (0.774)	2.194^{*} (0.806)
Urban	1	1
Rural	1.487 (0.506)	1.495 (0.576)
Secondary or less	1	1
Matric or equivalent	0.453^{*} (0.154)	0.610 (0.225)
Tertiary	0.108^{***} (0.054)	0.408 (0.271)
Matched	1	1
Underqualified	0.864 (0.278)	2.060 (1.078)
Overqualified	1.312 (0.439)	0.484 (0.216)
Full-time job	1	1
Part-time job	0.966 (0.307)	0.816 (0.262)
Legislators, senior officials and managers	-	0.160 (0.164)
Professionals	-	0.038^{**} (0.040)
Technicians and associate professionals	-	0.098^{*} (0.100)
Clerks	-	0.428 (0.300)
Service workers, shop and market sales workers	-	0.446 (0.252)
Skilled agricultural and fishery workers	-	0.527 (0.417)
Craft and related trades workers	-	0.108^{***} (0.070)
Plant and machine operators and assemblers	-	0.151^{*} (0.122)
Elementary occupations	-	1
Armed forces, unspecified and not elsewhere classified	-	0.287^{*} (0.158)
Observations	783	753

Source: SASAS 2013. Data are weighted using populations weights. Also controlling for province. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The reference categories are: male, black African, 16–24 years old, currently married, urban area, secondary or less, no overskilling, full-time job and elementary occupations.

The possible answers are: 'increased a lot' (1); 'increased' (2); 'stayed the same' (3); 'decreased' (4); 'decreased a lot' (5); and 'don't know' (8). The answers are recoded to three categories labelled 'increased', 'stayed the same' and 'decreased', while the 'don't know' response is coded as missing. Approximately 55% of the workers reported increased skill requirements at their job, 41% reported the same requirements, and only 4% reported decreased skill requirements. The change in skill requirements might be actual or perceived. However, the variable can be used as proxy for skills deficit. From the data, it is evident that respondents who answered positively to increased skill requirements are more likely to have received on-the-job training in the last 12 months than those who report the same or decreased skill requirements (58% versus 21%).

In Table 9, we see that undereducated or underskilled workers are indeed more likely to

Table 9: On-the-job training and increased skill requirements by education level and occupational-mismatch variables (percentages)

Occupational mismatch	Had training in the last 12 months	Reported increased skill requirements
Education level		
No schooling	43.8 (18.4, 72.9)	19.4 (3.6, 61.2)
Primary	20.6 (12.1, 32.9)	25.5 (16.4, 37.4)
Some secondary	25.3 (18, 34.3)	30.7 (23.1, 39.6)
Matric	41.6 (33.2, 50.4)	54 (44.9, 62.8)
Tertiary	66.3 (56.7, 74.6)	76.1 (66.8, 83.5)
X^2 test p-value	< 0.001	< 0.001
Educational mismatch		
Matched	34.6 (28.4, 41.4)	50.7 (43.6, 57.7)
Underqualified	49.2 (38.7, 59.8)	49.4 (38.9, 59.9)
Overqualified	37 (28, 47.1)	42.4 (33.1, 52.2)
X^2 test p-value	0.067	0.531
Skills mismatch		
No skill underutilisation	45.9 (40.4, 51.5)	55.3 (49.6, 60.9)
Strong skill underutilisation	11 (6.2,18.7)	19.7 (11.4, 32)
X^2 test p-value	< 0.001	< 0.001

Source: SASAS 2013. Data are weighted using populations weights. Confidence intervals in parentheses.

report that they have had training in the last 12 months (49% and 46%, respectively). However, the rates of additional training are relatively high among well-matched as well as overqualified employees (35–37%), perhaps implying that these workers have a job outside their field of study and benefit from extra training.

High rates of increased skill requirements are reported among all educational-mismatch categories, with approximately 50% of the well-matched and undereducated workers, and 42% of the overeducated, reporting increased skill requirements. The situation is slightly different for the overskilled workers, as only 20% of them report increased skill requirement, suggesting that perhaps the fact that they possess more skills than required for the job might help them cope with any new skill requirements. Mncwango (2016) presents descriptive results and suggests that better educated workers experience a greater increase in skill requirements. We further investigate the relationship between the two outcomes above and occupational mismatch and education, while controlling other demographic and socio-economic factors.

There is no significant correlation between gender, race, age or marital status and the likelihood of additional training. The relationship between having had on-the-job training and education appears to be positive, with the odds of training increasing as the education level increases. This result supports the hypothesis of education and training being complements rather than substitutes, as it appears that the better-educated workers receive more training. On the other hand, underqualified workers are three times more likely to receive additional training at work (OR = 3.104) than well-matched workers. The opposite holds for overeducated respondents, but the coefficient is not significant. Having a part-time job reduces one's chance of having on-the-job training, perhaps because part-time jobs might also be temporary and employers might be unwilling to invest in providing training for temporary employees. Workers who report strong skill underutilisation have lower odds of participating in training than workers who report weak or no skill underutilisation. Finally, it is evident that on-the-job training often corresponds to workers' needs for training, as respondents who have reported increased skill requirements since they started working in their job are also more likely to have had training in the past 12 months.

Table 10: Logistic regression of on-the-job training and increased skill requirements

Variable	Received training OR (s.e.)	Reported increase in skill requirements OR (s.e.)
Male	1	1
Female	0.806 (0.191)	1.099 (0.279)
Black African	1	1
Coloured	0.976 (0.383)	2.381** (0.761)
Indian	0.946 (0.484)	3.501* (1.961)
White	0.832 (0.306)	3.259** (1.167)
16–24 years	1	1
25–34 years	1.088 (0.510)	1.016 (0.422)
35–44 years	0.866 (0.453)	0.747 (0.325)
45–54 years	0.439 (0.240)	0.693 (0.333)
55+ years	0.480 (0.291)	1.529 (0.840)
Married	1	1
Previously married	1.325 (0.620)	1.924 (0.738)
Never married	0.965 (0.321)	1.964* (0.614)
Urban	1	1
Rural	0.832 (0.273)	1.021 (0.367)
Secondary or less	1	1
Matric or equivalent	1.785 (0.593)	2.672*** (0.752)
Tertiary	8.411*** (4.195)	7.527*** (4.115)
Matched	1	1
Underqualified	3.104** (1.187)	0.878 (0.399)
Overqualified	0.683 (0.257)	0.678 (0.288)
Full-time job	1	1
Part-time job	0.409** (0.117)	0.525* (0.142)
Weak skill underutilisation	1	1
Strong skill underutilisation	0.196*** (0.074)	0.285*** (0.090)
Reported increased skill requirements: No	1	-
Reported increased skill requirements: Yes	2.443*** (0.649)	-
Observations	753	753

Source: SASAS 2013. Data are weighted using populations weights. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Also controlling for province and occupational group.

When exploring the relationship between the likelihood of reporting increased skill requirements and the same factors, we see that black Africans are the least likely to report an increase. Never-married individuals have approximately three times higher odds of reporting an increase in skill demands than those who are married. Although educational mismatch is not significantly associated with this outcome, education appears to be positively associated. This highlights the lack of correspondence between skills and education and suggests that perhaps better-educated workers are more likely to report skill deficit and subsequently demand and receive training. Part-time and overskilled workers are less likely to report an increase in skill needs than full-time workers and respondents who do not report skill underutilisation.

4.7 Occupational mismatch and job satisfaction

Approximately 44% of the sampled workers report high job satisfaction and only 13% report low job satisfaction (weighted percentages are 41 and 15, respectively). Nevertheless, high job satisfaction is lower among overeducated workers than among well-matched and even undereducated workers, although the difference is not statistically significant (Table 11). On the other hand, we observe significant differences in job satisfaction by education level as well as by skill utilisation. Better-educated workers appear to be more satisfied with their jobs than less-educated workers, and overskilling is associated with lower job satisfaction.

Table 11: Job satisfaction by education level and occupational-mismatch measures (percentages)

	Job satisfaction	
Variable	**Low**	**High**
Education level		
No schooling	28.5 (10.3, 58)	9.7 (1.7, 40.9)
Primary	32 (20.7, 45.9)	27.7 (18, 40.1)
Some secondary	18 (11.5, 27.2)	34.7 (26.3, 44.1)
Matric or equivalent	11.9 (6.9, 19.6)	39.5 (31.4, 48.3)
Tertiary	7.2 (3.5, 14.4)	62 (51.5, 71.5)
X^2 test p-value	< 0.001	
Educational mismatch		
Well matched	15.6 (10.7, 22.1)	42.6 (35.8, 49.7)
Undereducated	14.1 (8.7, 22.1)	42.9 (33.8, 52.5)
Overeducated	16.1 (9.8, 25.3)	36.9 (28.4, 46.3)
X^2 test p-value	0.888	
Skills mismatch		
No skill underutilisation	7.5 (5.2, 10.7)	48.7 (43.3, 54.2)
Strong skill underutilisation	46.5 (35.3, 58)	11.1 (6.2, 18.9)
X^2 test p-value	< 0.001	

Source: SASAS 2013. Data are weighted using populations weights. Confidence intervals in parentheses.

When exploring the level of job satisfaction among various demographic groups, we see that white workers have the highest percentage of high job satisfaction (73%) in relation to all other race groups, and black Africans have the lowest (32%). High job satisfaction is reported more often among older workers, while the percentage is lower among never-married and rural residents as compared with married or urban residents (Table B4). There is a significant association between occupational group and reported level of job satisfaction (Table B5). Groups 1 (legislators, senior officials and managers), 2 (professionals) and 7 (craft and related trades workers) have the highest prevalence of high job satisfaction (66%, 61% and 62%, respectively). On the other hand, Groups 6 (skilled agriculture and fishery workers), 7 (clerks) and 9 (elementary occupation workers) report considerable levels of low job satisfaction (36%, 28% and 28%, respectively).

In order to control for other individual and job characteristics and identify which factors are associated with job satisfaction, we use ordered logistic regression to model the level of satisfaction. Including both educational and skill mismatch in the regression, as well as on-the-job training and an increase in skill requirements, will provide information on the net effect of each variable while controlling for the others. Certain job characteristics as reported by the workers themselves, such as secure job, high income, high opportunities for advancement, interesting job, useful-to-society job, chance for improving skills in the job, and fair pay and benefits are also important determinants (Table A9). Approximately 66% of the workers in the sample report that their job is secure, 68% of them report that their job is interesting, and 76% report that their job is useful to society. Forty per cent of the respondents claim that their opportunities for advancement are high in their current job, 68% that their job gives them a chance to improve their skills, and 50% that the pay and benefits which they receive are fair for the work they do. However, only 27% of the workers report that high income is a characteristic of their job.

In order to disentangle the effect of educational mismatch from the effect of skill mismatch, we run a model with only educational mismatch and then add skill mismatch. The third model includes participation in training and reporting of increased skill requirements, and the remaining job characteristics enter the regression in Model 4.

Table 12: Ordered logistic regressions of job-satisfaction level

Variable	Model 1	Model 2	Model 3	Model 4
Female	–0.038 (0.235)	0.047 (0.227)	0.072 (0.233)	0.151 (0.243)
Coloured	–0.146 (0.397)	–0.105 (0.371)	–0.187 (0.375)	–0.478 (0.340)
Indian	0.255 (0.400)	0.274 (0.400)	0.144 (0.421)	0.173 (0.460)
White	1.198*** (0.354)	1.284*** (0.373)	1.226*** (0.366)	1.120** (0.408)
25–34 years	0.326 (0.464)	0.389 (0.430)	0.376 (0.423)	0.419 (0.453)
35–44 years	0.049 (0.477)	0.166 (0.447)	0.188 (0.442)	0.612 (0.462)
45–54 years	0.203 (0.512)	0.174 (0.480)	0.275 (0.465)	0.822 (0.494)
55+ years	0.084 (0.581)	0.092 (0.575)	0.100 (0.573)	0.402 (0.611)
Previously married	0.149 (0.300)	0.204 (0.335)	0.148 (0.340)	0.012 (0.402)
Never married	–0.363 (0.267)	–0.166 (0.274)	–0.250 (0.266)	–0.061 (0.288)
Rural	–0.245 (0.280)	–0.186 (0.286)	–0.166 (0.286)	0.148 (0.333)
Matric or equivalent	0.012 (0.264)	–0.179 (0.261)	–0.389 (0.275)	–0.343 (0.284)
Tertiary	0.045 (0.472)	–0.169 (0.490)	–0.717 (0.502)	–1.032* (0.500)
Part-time job	–0.529* (0.256)	–0.619* (0.249)	–0.474 (0.260)	–0.246 (0.292)
Undereducated	–0.326 (0.343)	–0.176 (0.382)	–0.298 (0.375)	–0.035 (0.393)
Overeducated	0.613 (0.400)	0.471 (0.409)	0.586 (0.412)	0.831 (0.433)
Overskilled		–1.723*** (0.289)	–1.496*** (0.293)	–0.332 (0.325)
Received training	-		0.605* (0.251)	0.609* (0.285)
Reported increased skill requirements	-	-	0.543* (0.258)	0.547 (0.289)
Secure job	-	-	-	0.882** (0.297)
High income	-	-	-	0.995** (0.333)
High opportunities for advancement	-	-	-	0.162 (0.278)
Interesting job	-	-	-	1.677*** (0.278)
Useful-to-society job	-	-	-	0.305 (0.284)
Chance to improve skills	-	-	-	–0.114 (0.300)
Fair pay and benefits	-	-	-	0.765** (0.278)
N	751	751	751	724

Source: SASAS 2013. Data are weighted using populations weights. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Also controlling for province and occupational group.

Of the individual characteristics, only race appears to be consistently significant across the four models, with white workers being more likely to report higher job satisfaction. No significant differences are evident by gender, age group, geographical area and marital status.

Education level is not significant in Models 1 to 3 but becomes so in Model 4, where having tertiary education is associated with less job satisfaction. Although education is positively associated with job satisfaction in Model 1, the relationship changes when skill underutilisation is added in the regression (Model 2), and becomes significant after including job characteristics (secure job, etc.). Part-time employees are less satisfied with their jobs (Models 1 to 2), but the effect is not significant when we include participation in training and reported increase in skill requirements. Educational mismatch is not significantly related to job satisfaction. However, skills mismatch is, with overskilled workers being less satisfied with their jobs (Models 2 to 3). Nevertheless, it is the perceived job characteristics that matter the most when it comes to job satisfaction: workers who have training, a secure job, a high income, an interesting job, or fair pay and benefits are more satisfied that those who do not have a job with these quality-indicators.

5 CONCLUSIONS AND IMPLICATIONS FOR SKILLS PLANNING

This paper addresses both educational mismatch and skills imbalances in order to understand the phenomenon of occupational mismatch in the South African labour market. The analysis is based on a unique data set (South African Social Attitudes Survey [SASAS] 2013) which, for the first time, included a number of questions on both objective and subjective measures of overeducation and overskilling in South Africa. In this section, we summarise the main findings, discuss the study limitations, and link the findings to policy implications.

Qualification mismatch is quantified using an objective measure obtained by way of the normative or job analysis (JA) method, as it might be of higher quality owing to the fact that it is conceptualised by job analysts (Flisi et al. 2014) in order to compare. The prevalence of educational mismatch is high in South Africa, with more than half of South African workers being mismatched. In particular, 27% of them are undereducated and 26% of them are overeducated, a finding that is consistent with the results of Beukes et al. (2016). Educational mismatch is not significantly related to gender, age group, marital status or area of residence. As expected, employees with tertiary education or in a part-time job have a greater chance of being overeducated. Educational mismatch also varies significantly by occupational group: Group 1 (legislators, senior officials and managers) has the highest prevalence of underqualification, while Group 9 (elementary occupations) has the highest prevalence of overqualification.

One of the main questions we try to answer is whether educational mismatch implies skills mismatch, or whether there is only a weak relationship between the two as previously shown (Allen & Van der Velden, 2001). A skills-mismatch indicator defined as skills underutilisation or overskilling is created though a subjective question in the SASAS 2013. The question identifies whether workers perceive that they are fully utilising their knowledge and skills in their jobs. Twenty percent of the employed are estimated to be overskilled for their job, a percentage that is much lower than the educational-mismatch percentage in the population. Overeducation does not necessarily mean overskilling in the South African workforce, as the overskilling prevalence is not significantly different across the educational-mismatch groups. However, significant differences in the prevalence of skills underutilisation are to be observed among occupational groups, with the highest rate of overskilling reported among skilled agricultural and fishery workers (51%), and the second-highest among workers in elementary occupations (35%). In the regressions for the skills-mismatch measure, marital status and education are significant predictors. However, only marital status remains significant after controlling for workers' occupation group.

Next, we investigated the prevalence of on-the-job training and increased skill requirements, as well as their relationship with education level and occupational mismatch. On-the-job training has been suggested as a solution to qualification mismatch, and we find that underqualified workers are indeed three times more likely to participate in training than well-matched workers. Education level is also associated with higher odds of training, while having a part-time job and being overskilled are associated with lower odds of training.

Van Smoorenburg and Van der Velden (2000) discuss how two labour market theories, the *human-capital theory* and the *matching theory*, can interpret the effect of on-the-job training on skills. In human-capital theory, training increases productivity, since it is regarded as adding to human capital and is assumed to complement formal education. Highly educated individuals with an increased learning ability will be more likely to receive and benefit from training. Large firms will also be more likely to invest in training employees owing to the economies of scale with regard to training costs. Part-time and temporary employees have less chance to participate in training, as employers would rather invest in training permanent and full-time staff. The matching theory is consistent with the assumption that training and education are substitutes and that additional training will benefit undereducated workers. Our results suggest that both theories are plausible and that a certain overlap between them exists. However, not all important factors are available in our data set, which limits further inferences.

The question about workers facing increased skill requirements since they started the job is also interesting in itself, as it suggests a certain skills mismatch, skills obsolescence or skills deficit that perhaps was not evident when the worker was initially employed. This might lead to poor performance on the part of workers which would endanger the security of their jobs. The phenomenon might be more severe in sectors that heavily rely on advanced technology (Allen & De Grip 2007). The logistic regression estimating increased skill requirements showed that all populations groups are more likely than black Africans to experience this. Level of education appears to be positively associated with reporting increased skill requirements. Part-time workers are less likely to report increased skill requirements than full-time workers, as are respondents with strong skill underutilisation as opposed to those who are not overskilled.

The last outcome of interest is job satisfaction and its relationship with education levels, educational mismatch and skills mismatch. Four different regression models are fitted in order to identify the determinants of job satisfaction. We find that white workers are consistently more likely to have high job satisfaction compared with black African workers. Part-time employees tend to be less satisfied with their jobs than full-time employees. The coefficient for level of education is significant only in the last model, where we control for a variety of job characteristics. There is no evidence that qualification mismatch is correlated with job satisfaction. Skill underutilisation, however, is negatively associated with job satisfaction, but the effect diminishes when other job characteristics are added: it appears that having a secure or interesting job, high income, or fair pay and benefits does increase job satisfaction and that this explains virtually all of the association between skills underutilisation and job satisfaction. In the South African workforce, therefore, skills underutilisation appears to be a strong proxy for low-skilled and low-paid work, which, in turn, is linked with a lower level of skills development and a lower probability of having received skills training.

This study is the first in-depth analysis of occupational mismatch in South Africa and our findings have important implications for labour market research and policy. It is also the first study that obtains a variety of occupational-mismatch indicators and attempts to compare them. We show that qualification mismatch is prevalent in South Africa, and we provide evidence that, as in other contexts, it may not be closely associated with a skills mismatch. The difference in the prevalence of educational mismatch and skills mismatch suggests that overqualification may conceal a degree of skill heterogeneity. Finally, skills mismatch may be a better predictor for training participation and job satisfaction than educational mismatch. This is an important finding, particularly given the extremely high level of inequality in the South African labour market in terms of both earnings and access to education and training.

The collaboration and involvement of all relevant parties are required in order to address occupational mismatch: workers, employers, and government. As education and training play an important role in labour market imbalances, a well-functioning education system incorporating adult education and training is the most important tool to tackle occupational mismatch. In addition to the policy recommendations outlined in Reddy et al. (2016), we discuss a few other potentially useful policies.

As the evidence suggests, adult learning and on-the-job training constitute a potential remedy with regard to occupational mismatch. Both employed and unemployed individuals should be targeted, and it is imperative that training is up to date as far as technological change is concerned. Underqualified workers, in particular, may benefit from participating in training, as it can help them acquire new skills. Training should also target better-educated employees, as it might be considered a complement to their education and beneficial for their professional development. Training is effective against skill obsolescence, even for overskilled workers when their skills become outdated.

Underqualified individuals in high-skilled positions such as Occupational Group 1 (legislators, senior officials and managers) also need to receive appropriate training, but their work experience, on-the-job learning as well as other informal learning need to be taken into account when assessing their skills. Overqualified workers might lack the skills corresponding to their qualifications or be skilled in other fields not required by their employer. Appropriate career guidance would be helpful for these workers in order to match their skills to specific jobs and, more generally, to link labour market supply and demand. In South Africa, the quality of education varies greatly among educational institutions, which might lead to skills deficit for workers from disadvantaged backgrounds. Therefore, an effort should be made to ensure quality education for all.

Our study has certain limitations, with the major one being the small sample size and the number of missing values for some questions. More detailed information on education and training backgrounds, as well as important labour market variables, is not available in SASAS 2013. Some of the key variables which are missing from the analysis, for example, include: field of study, duration of tenure in current job, past work experience, employment sector, type of employment (permanent/temporary, formal/informal), firm-size, migration status of the worker, and job mobility. Moreover, the particular module on attitudes to work was only used once; hence we cannot obtain information about changes in time or trends of occupational mismatch and whether it is a persistent or temporary phenomenon. Finally, most of the variables explored are subjective evaluations and they may suffer from measurement bias.

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REFERENCES

Alba-Ramirez, A. (1993). Mismatch in the Spanish labor market: Overeducation? *Journal of Human Resources*, 259–278.

Allen, J. & De Grip, A. (2007). Skill obsolescence, lifelong learning and labor market participation. ROA-RM-2007/6. Maastricht: Research Centre for Education and the Labour Market.

Allen, J. & De Weert, E. (2007). What do educational mismatches tell us about skill mismatches? A cross-country analysis. *European Journal of Education*, 42(1), 59–73.

Allen, J. & Van der Velden, R. (2001). Educational mismatches versus skill mismatches: Effects on wages, job satisfaction, and on-the-job search. *Oxford Economic Papers*, 53(3), 434–452.

Allen, J., Van der Velden, R. & Levels, M. (2013). Skill mismatch and use in developed countries: Evidence from the PIAAC Study. RM/13/061. Maastricht: Research Centre for Education and the Labour Market.

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

Bauer, T. K. (2002). Educational mismatch and wages: A panel analysis. *Economics of Education Review*, 21(3), 221–229.

Berg, I. (1970). *Education for jobs: The great training robbery*. New York: Praeger, 1970.

Beukes, R., Fransman, T., Murozvi, S. & Yu, D. (2016). Underemployment in South Africa. Stellenbosch Economic Working Paper 06/16. Stellenbosch: Bureau for Economic Research, University of Stellenbosch.

Chevalier, A. (2003). Measuring over-education. *Economica*, 70(279), 509–531.

Daniels, R. (2007). Skills shortages in South Africa: A literature review. DPRU Working Paper, No. 07/121.

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

Desjardins, R. & Rubenson, K. (2011). An analysis of skill mismatch using direct measures of skills. OECD Education Working Papers. Paris: Organisation for Economic Co-operation and Development.

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

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

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

Flisi, S., Goglio, V., Meroni, E. C., Rodrigues, M. & Vera-Toscano, E. (2016). Measuring occupational mismatch: Overeducation and overskill in Europe – evidence from PIAAC. *Social Indicators Research*, 1–39.

Green, F. & McIntosh, S. (2007). Is there a genuine under-utilisation of skills amongst the over-qualified? *Applied Economics*, 39(4), 427–439.

Green, F. & Zhu, Y. (2010). Overqualification, job dissatisfaction, and increasing dispersion in the returns to graduate education. *Oxford Economic Papers*, 62(4), 740–763.

Groot, W. (1993). Overeducation and the returns to enterprise-related schooling. *Economics of Education Review*, 12(4), 299–309.

Halaby, C. (1994). Overeducation and skill mismatch. *Sociology of Education*, 67(1), 47–59.

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

Hartog, J. & Oosterbeek, H. (1988). Education, allocation and earnings in the Netherlands: Overschooling? *Economics of Education Review*, 7(2), 185–194.

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

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

Mavromaras, K., McGuinness, S. & Wooden, M. (2007). Overskilling in the Australian labour market. *Australian Economic Review*, 40(3), 307–312.

McGuinness, S. (2006). Overeducation in the labour market. *Journal of Economic Surveys*, 20(3), 387–418.

McGuinness, S. & Sloane, P. J. (2011). Labour market mismatch among UK graduates: An analysis using REFLEX data. *Economics of Education Review*, 30(1), 130–145.

Mncwango, B. (2016). Public attitudes to work in South Africa. LMIP report 16. Labour Market Intelligence Partnership.

Perry, A., Wiederhold, S. & Ackermann-Piek, D. (2014). How can skill mismatch be measured? New approaches with PIAAC. *Methods, Data, Analyses: A Journal for Quantitative Methods and Survey Methodology*, 8(2), 137–174.

Quintini, G. (2011a). Right for the job: Over-qualified or under-skilled? OECD Social, Employment and Migration Working Papers, No. 120. OECD Publishing.

Quintini, G. (2011b). Over-qualified or under-skilled: A review of existing literature. OECD Social, Employment and Migration Working Papers, No. 121. OECD Publishing.

Reddy, V., Bhorat, H., Powell, M., Visser, M. & Arends, A. (2016). Skills supply and demand in South Africa. LMIP Publication. Human Sciences Research Council, Pretoria.

Roberts, B., Wa Kivilu, M. & Davids, Y. (2010). *South African attitudes: Reflection on the Age of Hope.* Cape Town: HSRC Press.

Sloane, P. (2003). Much ado about nothing? What does the overeducation literature really tell us. In: F. Büchel, A. de Grip & A. Mertens (eds). *Overeducation in Europe. Current issues in Theory and Policy.* Cheltenham: Edward Elgar. pp. 11–45.

Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics*, 355–374.

Stats SA (Statistics South Africa). *Quarterly Labour Force Survey: Quarter 1*. Available at: http://www.statssa.gov.za/publications/P0211/P02111stQuarter2016.pdf.

Van Smoorenburg, M. S. M. & Van der Velden, R. K. (2000). The training of school-leavers: Complementarity or substitution? *Economics of Education Review*, 19(2), 207–217.

Verdugo, R. R. & Verdugo, N. T. (1989). The impact of surplus schooling on earnings: Some additional findings. *Journal of Human Resources*, 24(4), 629–643.

Verhaest, D. & Omey, E. (2006a). Measuring the incidence of over- and undereducation. *Quality and Quantity*, 40(5), 783–803.

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

Vieira, J. A. C. (2005). Skill mismatches and job satisfaction. *Economics Letters*, 89(1), 39–47.

APPENDIX A

Sample descriptives for variables of interest

Table A1: Sample characteristics

Variable	N (%)
Gender	
Male	432 (51)
Female	412 (49)
Missing	0
Race	
Black	450 (53)
Coloured	156 (19)
Indian	86 (10)
White	150 (18)
Missing	2
Age	
16–24 years old	91 (11)
25–34 years old	237 (28)
35–44 years old	242 (29)
45–54 years old	162 (19)
55+ years old	107 (13)
Missing	5
Education	
No schooling	19 (2)
Primary or less	103 (13)
Some secondary	226 (27)
Matric or equivalent	279 (34)
Tertiary	199 (24)
Missing	18
Marital status	
Married	398 (48)
Previously married	110 (13)
Never married	329 (39)
Missing	7
Area of residence	
Urban area	676 (80)
Rural area	168 (20)
Missing	0
Personal income	
Less than R1 500	185 (28)
R1 501–R5 000	233 (35)
R5 001 or more	243 (37)
Missing	183
Job type	
Full-time	605 (72)
Part-time	239 (28)
Missing	0
Total	**844**

Source: SASAS 2013. Data are unweighted.

Table A2: Sample distribution by province

Province	N (%)
Western Cape	132 (16)
Eastern Cape	88 (10)
Northern Cape	60 (7)
Free State	65 (8)
KwaZulu-Natal	172 (20)
North West	58 (7)
Gauteng	130 (15)
Mpumalanga	63 (7)
Limpopo	76 (9)

Source: SASAS 2013. Data are unweighted.

Table A3: Major occupational group

Major occupation group	N (%)
1. Legislators, senior officials and managers	53 (7)
2. Professionals	122 (15)
3. Technicians and associate professionals	63 (8)
4. Clerks	61 (8)
5. Service workers and shop and market sales workers	100 (12)
6. Skilled agricultural and fishery workers	19 (2)
7. Craft and related trades workers	59 (7)
8. Plant and machine operators and assemblers	50 (6)
9. Elementary occupations	171 (21)
0. Armed forces, occupations unspecified and not elsewhere classified	109 (14)
Missing	37

Source: SASAS 2013. Data are unweighted.

Table A4: SASCO 2003 skill level (unweighted)

Skill level	N (%)
1	177 (22)
2	389 (48)
3	64 (8)
4	177 (22)
Missing	37

Source: SASAS 2013. Data are unweighted.

Table A5: Minimum level of education required for the respondent's job

Required education level	N(%)
No schooling	153 (19)
Primary	34 (4)
Some secondary	138 (17)
Matric or equivalent	256 (32)
Tertiary	225 (28)
Missing	38

Source: SASAS 2013. Data are unweighted.

Table A6: Subjective skills-mismatch questions

The work I do makes full use of my knowledge and skills.	**N(%)**
Strongly agree	181 (22)
Agree	370 (46)
Neither agree nor disagree	98 (12)
Disagree	111 (14)
Strongly disagree	44 (6)
Can't choose	4 (0.5)
Missing	36
To what extent is your expertise relevant to what you do in your job every day?	
Completely relevant	201 (25)
To a great extent	240 (30)
To some extent	213 (26)
Not at all relevant	76 (9)
Have not received any training	69 (9)
Do not know	11 (1)
Missing	34

Source: SASAS 2013. Data are unweighted.

Table A7: Additional training and increased skill requirements

Over the past 12 months, have you had any training to improve your job skills (either at the workplace or somewhere else)?	**N (%)**
Yes	333 (41)
No	472 (59)
Missing	39
Since you began working on your current job, have the overall skill requirements of the position: increased, stayed the same or decreased?	N (%)
Increased a lot	133 (16)
Increased	305 (38)
Stayed the same	319 (39)
Decreased	25 (3)
Decreased a lot	7 (1)
Do not know	21 (3)
Missing	34

Source: SASAS 2013. Data are unweighted.

Table A8: Job satisfaction

How satisfied are you in your (main) job?	N (%)
Completely satisfied	133 (16)
Very satisfied	222 (27)
Fairly satisfied	221 (27)
Neither satisfied nor dissatisfied	61 (8)
Fairly dissatisfied	64 (8)
Very dissatisfied	70 (9)
Completely dissatisfied	37 (5)
Can't choose	2 (0)

Source: SASAS 2013. Data are unweighted.

Table A9: Other job characteristics (recoded)

My job is secure.	**N (%)**
Agree	529 (66)
Neither agree nor disagree	77 (10)
Disagree	199 (24)
My income is high.	
Agree	215 (27)
Neither agree nor disagree	146 (18)
Disagree	443 (55)
My opportunities for advancements are high.	
Agree	320 (40)
Neither agree nor disagree	144 (18)
Disagree	335 (42)
My job is interesting.	
Agree	546 (68)
Neither agree nor disagree	91 (11)
Disagree	166 (21)
My job is useful to society.	
Agree	601 (76)
Neither agree nor disagree	89 (11)
Disagree	101 (13)
My job gives me a chance to improve my skills.	
Agree	548 (68)
Neither agree nor disagree	92 (12)
Disagree	164 (20)
The pay and benefits I receive are fair for the work I do.	
Agree	406 (50)
Neither agree nor disagree	105 (13)
Disagree	294 (37)

Source: SASAS 2013. Data are unweighted.

Table A10: Proportion of correspondence between educational-mismatch measures

Measure	JA	MODE2	MEAN2	ISA
JA	1	0.62	0.54	0.48
MODE2	0.62	1	0.62	0.49
MEAN2	0.54	0.62	1	0.48
ISA	0.48	0.49	0.48	1

Source: SASAS 2013. Data are unweighted.

Table A11: Spearman rank correlation between occupational-mismatch measures

Measure	JA	ISA	MODE2	MEAN2	SU	SR
JA	1	0.147*	0.336*	0.133*	–0.005	–0.052
ISA	0.147*	1	0.123*	0.002	0.184*	–0.190*
MODE2	0.336*	0.123*	1	0.269*	0.005	0.002
MEAN2	0.133*	0.002	0.269*	1	–0.023	0.061
SU	–0.005	0.184*	0.005	–0.023	1	–0.323*
SR	–0.052	–0.190*	0.002	0.061	–0.323*	1

Source: SASAS 2013. Data are unweighted. Significance level of 5%.

APPENDIX B

Additional population statistics and regression results

Table B1: Overskilling by educational-mismatch group (percentages)

Educational mismatch	Strong skill underutilisation
Well matched	20.2 (14.8, 27)
Undereducated	17.8 (11.9, 25.7)
Overeducated	22 (14.8, 31.4)

Source: SASAS 2013. Data are weighted using populations weights. Confidence intervals in parentheses.

Table B2: Qualification-mismatch (JA) prevalence by relevant factors (row percentages)

Variable	Matched	Underqualified	Overqualified
Male	47.6 (40.9, 53.8)	29.8 (24.2, 36.6)	22.6 (17.6, 28.6)
Female	44.3 (37, 50.9)	23.5 (17.9, 28.8)	32.2 (27, 40.2)
Black	46.1 (39.5, 51.6)	29.3 (23.6, 35.2)	24.6 (20.5, 31.2)
Coloured	54.4 (42.5, 65.8)	21.4 (14.2, 30.6)	24.2 (16.1, 34.8)
Indian	51.3 (36, 68.5)	41.5 (24.5, 59)	7.1 (3.4, 13.5)
White	40.5 (30.2, 51.6)	20.1 (13.7, 29.4)	39.4 (29, 50.2)
16–24 years old	47.2 (29.5, 59.8)	31.4 (18.6, 48.6)	21.4 (14.1, 38.3)
25–34 years old	48.1 (39.7, 56.6)	23.3 (15.6, 30.8)	28.6 (22.5, 37.9)
35–44 years old	48.7 (40.3, 58)	23.8 (16.9, 32.2)	27.5 (19.6, 36.4)
45–54 years old	46.2 (35, 55.6)	33.5 (25.8, 45.7)	20.2 (12.7, 29.5)
55+ years old	35.4 (24.9, 49.7)	33.5 (22.1,45.6)	31.1 (19.7, 44.7)
Married	43.7 (36.9, 50.6)	29.6 (22.9, 36.5)	26.7 (21.2, 34.1)
Previously married	42.7 (30, 55.1)	34.2 (22.7, 48)	23.1 (13.7, 37.7)
Never married	49.8 (41.8, 56.5)	24.3 (18.7, 31.4)	25.9 (20.5, 33.3)
Rural area	43.4 (33.4, 54)	32.9 (23.6, 43.8)	23.7 (15.9, 33.7)
Urban area	47.1 (41.6, 52.6)	25.9 (21.2, 31.2)	27 (22.4, 32.3)
R0–R1 500	37.9 (28.2, 48.7)	29.8 (19.7, 42.2)	32.3 (22.6, 43.8)
R1 501–R5000	50.3 (41.6, 59.1)	24.3 (18, 32)	25.4 (18.2, 34.2)
R5 001+	43.5 (34.9, 52.6)	30.7 (22.4, 40.4)	25.7 (18.7, 34.3)
Western Cape	59 (47.6, 69.5)	20.3 (13.4, 29.6)	20.6 (13.3, 30.6)
Eastern Cape	27 (17.4, 39.4)	31.1 (18.8, 46.8)	41.9 (28.8, 56.3)
Northern Cape	60.6 (42.8, 75.9)	20 (9.3, 37.9)	19.4 (9.9, 34.5)
Free State	59.6 (43.5, 73.9)	12.5 (5.2, 29.6)	27.9 (16.7, 42.8)
KwaZulu-Natal	46.7 (35.9, 57.8)	28 (19.4, 38.4)	25.4 (16.9, 36.3)
North West	56.1 (39.9, 71.1)	24.5 (13.6, 40.2)	19.4 (9.9, 34.5)
Gauteng	35.3 (25, 47.3)	34.1 (22.5, 48)	30.5 (20, 43.6)
Mpumalanga	44.9 (29.8, 61.1)	36.1 (22.5, 52.4)	18.9 (8.1, 38.2)
Limpopo	53.1 (39.3, 66.5)	26 (15.7, 39.9)	20.9 (12.2, 33.4)
Total	**46.3 (41.2, 50.7)**	**27.3 (23, 31.8)**	**26.4 (22.8, 31.3)**

Source: SASAS 2013. Data are weighted using populations weights. Confidence intervals in parentheses. There are 179 missing values for personal income. Race and province are significantly associated with educational mismatch at the 5% level.

Table B3: Skill-underutilisation prevalence by relevant factors (percentages)

Variable	Strong skill underutilisation
Male	18.2 (13.4, 24.1)
Female	23.2 (17.1, 30.7)
Black	24.4 (19.4, 30.2)
Coloured	18.8 (8, 38.2)
Indian	6.9 (3.1, 14.6)
White	6.7 (2.9, 14.8)
16–24 years old	20.6 (9.4, 39.2)
25–34 years old	23.4 (17, 31.2)
35–44 years old	21.7 (14.3, 31.5)
45–54 years old	15.9 (9.5, 25.6)
55+ years old	13.6 (7, 24.7)
Married	12.9 (8.9, 18.4)
Previously married	20 (10.9, 33.6)
Never married	26.7 (20.2, 34.5)
Rural area	17.8 (13.6, 22.9)
Urban area	29.9 (21.1, 40.6)
R0–R1500	33.2 (23.7, 44.3)
R1 501–R5 000	22.2 (15.7, 30.3)
R5 001+	4.8 (2.2, 10.1)
Western Cape	15.3 (7.5, 28.7)
Eastern Cape	21.3 (12.4, 34.2)
Northern Cape	10.1 (4.1, 22.8)
Free State	32.9 (18.4, 51.6)
KwaZulu-Natal	17.4 (10.2, 28.1)
North West	16.4 (7.9, 31.1)
Gauteng	20.9 (12.4, 33)
Mpumalanga	21.8 (10.5, 39.7)
Limpopo	28.7 (18.5, 41.6)
Total	**20.2 (16.3, 24.7)**

Source: SASAS 2013. Data are weighted using populations weights. There are 179 missing values for personal income. Confidence intervals in parentheses. Race, marital status, area and personal income are significantly associated with skills mismatch at the 5% level.

Table B4: Job satisfaction by relevant factors (percentages)

	Job satisfaction	
	Low (CI)	**High (CI)**
Male	16 (11.7, 21.6)	42.1 (35.8, 48.7)
Female	14.2 (9.3, 21.1)	39.7 (33.1, 46.8)
Black	20 (15.6, 25.3)	32 (26.5, 38.2)
Coloured	12.1 (3.3, 35.3)	43 (31.8, 55)
Indian	4 (1.5, 10.2)	57.9 (41.9, 72.4)
White	0.9 (0.2, 3.9)	73.4 (61.4, 82.6)
16–24 years old	20.9 (10, 38.6)	36.7 (23.3, 52.5)
25–34 years old	17 (11.8, 23.9)	37.6 (29.4, 46.6)
35–44 years old	13.6 (8, 22.4)	40.1 (31.7, 49)
45–54 years old	13.9 (7.4, 24.5)	49.4 (39, 60)
55+ years old	10.6 (4.5, 22.8)	48.5 (35.4, 61.9)
Married	10.2 (6.5, 15.5)	49.5 (42.3, 56.7)
Previously married	7.7 (3.3, 17)	40 (27.8, 53.6)
Never married	21.5 (15.6, 28.8)	33.8 (27, 41.4)
Rural area	12.7 (9, 17.4)	45.2 (39.7, 50.7)
Urban area	25.7 (17.8, 35.4)	25.7 (17.7, 35.9)
Total	**15.3 (11.9, 19.5)**	**41.2 (36.5, 46)**

Source: SASAS 2013. Data are weighted using populations weights. Confidence intervals in parentheses. Race, marital status and geographical area are significantly associated with job satisfaction at the 5% level.

Table B5: Job satisfaction by occupational groups

Occupation group	% low (CI)	% high (CI)
1. Legislators, senior officials and managers	8.6 (2.6, 24.8)	66.2 (49, 80)
2. Professionals	5.9 (2, 15.7)	60.6 (44.7, 74.5)
3. Technicians and associate professionals	12.2 (4, 31.9)	57.6 (40.1, 73.4)
4. Clerks	28.1 (10.8, 55.8)	27.8 (13.8, 48.1)
5. Service workers and shop and market sales workers	15.7 (7.8, 29.2)	37.8 (26.4, 50.8)
6. Skilled agricultural and fishery workers	36.3 (16.2, 62.8)	12.4 (4.1, 32.1)
7. Craft and related trades workers	4.4 (1.3, 13.8)	61.7 (45.3, 75.8)
8. Plant and machine operators and assemblers	13.1 (5.5, 18)	43.6 (25.5, 63.7)
9. Elementary occupations	28.1 (19, 39.4)	20.7 (13.5, 30.3)
0. Armed forces, unspecified or unclassified	6.5 (2.8, 14.1)	40.6 (29.1, 53.3)

Source: SASAS 2013. Data are weighted using populations weights. Confidence intervals in parentheses. Significant relationship at the 5% level.