Southern Africa Labour and Development Research Unit

Duration of unemployment in youth transitions from schooling to work in Cape Town

by

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Abstract

The transition from school to work marks the beginning of the labour market experience of youth. If smooth and efficient, it can be a springboard to a successful career. However, it often is not a smooth transition and youth can be trapped in unemployment for relatively long periods. This paper makes use of a youth panel data set, the Cape Area Panel Survey (CAPS), which is rich in information about job search and timing of employment to illuminate the issue of youth transition to the labour market. Utilising month-by-month calendar entries, we are able to chart detailed labour market activity of youth in Cape Town. Following this, the nature and degree of duration dependence in the Cape Town labour market is examined using survival analysis. Furthermore, we examine whether the hazard of exiting the unemployment state is positive, negative or constant. Economic theory suggests that where the unemployment rate is very high, duration dependence should be negative, meaning that the likelihood of exiting a state of unemployment decreases with the length of the unemployment spell. The reasoning behind this postulation is that in an environment of high unemployment, the discouraged worker effect is prevalent, and it is likely that workers will decrease their search intensity or resort to a more passive means of job search. These factors could serve to decrease the exit probability of the unemployed.

1. Introduction

The transition from school to work marks the beginning of the labour market experience of youth. If smooth and successful, it can be a springboard to a successful career. However, it often is not a smooth transition and youth can be trapped in unemployment for relatively long periods. There are significant racial differences in securing employment among youth at a national level. This paper makes use of a youth panel data set, the Cape Area Panel Survey (CAPS), which is rich in information about job search and timing of employment to illuminate the issue of youth transition to the labour market. Utilising month-by-month calendar entries, one is able to chart detailed labour market activity of youth in Cape Town. Following this, the nature and degree of duration dependence in the Cape Town labour market is examined using survival analysis. Specifically what will be examined is whether the hazard of exiting the unemployment state is positive, negative or constant. Economic theory suggests that duration dependence should be negative, meaning that the likelihood of exiting a state of unemployment decreases with the length of the unemployment spell. The reasoning behind the theory is that in an environment of high unemployment, the discouraged worker effect is prevalent, and it is likely that workers will decrease their search intensity, or resort to a more passive means of job search. These factors could serve to decrease the exit probability of the unemployed.

Surveying the CAPS data, it is established that White youth make a relatively smooth transition from schooling to work while African and Coloured youth are clearly much less successful, though to differing degrees. Therefore the differences in employment outcomes between Africans and Coloureds are viewed to be of particular interest as these two groups are alike in many respects related to their socioeconomic profiles, yet they are very different in terms of labour market outcomes. The analysis in this paper will therefore focus on these two race groups.

In order to position this study of Cape Town within the broader context of South Africa as a whole, the analysis begins by comparing Cape Town and South Africa as a whole using the micro sample of the 2001 census. The 2001 census data is a good choice because it lies closer to the period when the CAPS respondents were first surveyed in 2002. Following this exercise, the month-by-month calendar data is used to reflect diagrammatically the job search and employment activities of African and Coloured youth in Cape Town. The analysis then proceeds to an examination of duration dependence within this labour market. After careful interrogation of the shape of the hazard function, the conclusion reached is that the proportional hazards assumption does hold, following which the Weibull model is fitted to the data, controlling for heterogeneity. A key conclusion reached in this analysis is that there is positive duration dependence in the Cape Town labour market.

2. Youth unemployment in Cape Town in a national perspective

By way of contextualising CAPS, attention is now directed at a comparison of Cape Town and the rest of South Africa using the 2001 census 10% micro-data set. This is the largest data set available for a post-2000 analysis. The comparison is restricted to the age ranges 14-22 years old because this coincides with the age ranges of the youth that were included in the first wave of CAPS. According to the 2001 census, Cape Town makes up just over 6% of South Africa's population and 11.3% of the urban population in the 14 to 22 age group.

Table 1 compares a population breakdown by race for this age cohort in Cape Town and the rest of South Africa. It shows that Africans make up the overwhelming majority (82%) of the South African population while the shares of Coloureds and Whites are almost equal at 8% and 7% respectively. The composition of the Cape Town population is very different, however. Almost half of the population of Cape Town is Coloured, while 35% is African and 14% is White. Comparison of Cape Town's racial composition with that of the rest of the urban areas indicates that Cape Town's unique history has resulted in something of a reshuffling of the African and Coloured race groups. The racial profile of the rest of urban South Africa is similar to the profile of the country as a whole but the shares of Africans and Whites are affected by the overrepresentation of Africans in rural areas.

**Table 1. Population percentages of youth aged 14-22,
Cape Town versus the rest of South Africa**

Population Group	Cape Town	Rest of South Africa		Total South Africa
		Urban	All	
Black African	35%	74%	85%	82%
Coloured	49%	10%	6%	8%
Indian or Asian	2%	5%	2%	2%
White	14%	12%	7%	7%
Total	100%	100%	100%	100%

Source: 10% Microsample of the 2001 Census
Notes: Own calculation using survey weights

Further analysis of the differences between Cape Town and the rest of South Africa reveals the following key points: while youth unemployment in Cape Town may be lower than in other parts of South Africa, it follows the same patterns. Most importantly, the role of education in a successful move into employment seems to be very similar in the urban Cape Town labour market as it is elsewhere in the country. Moreover, the racial marker is as strong in Cape Town as it is elsewhere. At the same time, the presence of a substantial Coloured population occupying an intermediate position between Africans and Whites allows for additional subtlety in exploring the interactions between race, education and the labour market. Thus, there is real interest in what can be learned from the school/labour market transitions and the unemployment/employment transitions of Cape Town's youth.

3. Transitions between school and the labour market in the Cape Area Panel Study

While much can be learned from analysis of large cross-sectional data sets such as the census, these data sets provide only a limited picture of the experience of young people when they first enter the labour market. In this section, advantage is taken of the Cape Area Panel Study (CAPS), to get a richer picture of the dynamics of transitions from school to work.   Wave 1 of CAPS, which was collected in 2002, included 4,752 young people aged 14-22, living in 3,304 households. CAPS was designed as a stratified two-stage clustered sample with stratification on the predominant population group living in each sample cluster. CAPS youth respondents were interviewed a second time in either 2002 or 2003, a third time in 2005, and a fourth time in 2006. The analysis below uses data from all these waves, taking advantage of the retrospective reports on monthly employment and job search provided in each wave.

Looking at transitions from school to work using both the retrospective histories from Wave 1 and the longitudinal data on work and school reported in 2003, 2004, and 2005, a number of interesting findings emerge. There are large differences in the transitions from school to work across population groups. While being in school without working is by far the predominant activity for all three groups at age 14, by age 17 some sharp differences have emerged. Significant proportions of White males are working during years when they are still in school, with 45% of White males in the work and school category at age 17. In contrast, the percentage of African males who work during years when they are still in school is negligible, never exceeding 5%. The transition from school to work for Coloured males is characterised more by a sharper transition than it is for either White or African males. Relatively small proportions of Coloured males work during the years they are in school but by age 18 the proportion working exceeds the proportion enrolled. The proportion of Coloured males enrolled in school drops below that of both Africans and Whites by age 16.
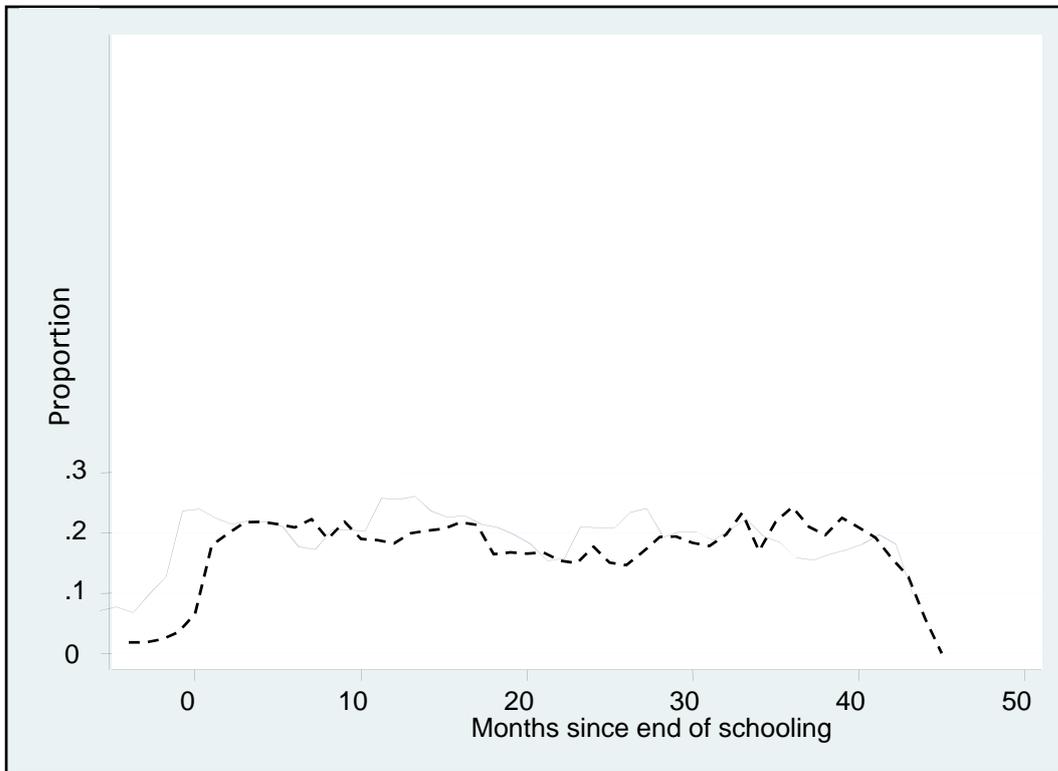
3.1 Job Search in the School to Work Transition

As mentioned above, one of the unique features of the CAPS data is that monthly data has been collected on school, work, and job search covering the period from August 2002 through the time of the Wave 4 interview in 2005. Starting with job search, Figure 1, for example, shows the proportions of African and Coloured males searching in each month after the end of studies. Data for four months before the end of studies are also included to give an indication of search activity immediately before the end of schooling.

It can be seen that a higher proportion of Coloured males search for work just prior to and just after stopping school. The proportions are then quite similar after that. Generally for both races, the proportion of individuals searching for work does not exceed 25% in each month. The reason for this pattern could either be that as some individuals find jobs others lose their jobs and begin searching while others become discouraged and stop searching. It is interesting, however, that the proportions searching do not start out relatively high. A similar pattern is apparent for females, although in this case the higher proportion of Coloured females searching is observed up to 10 months after leaving school. What is

evident from this analysis is that there is not a great divergence in search activity by race or by gender amongst Coloured and African youth in Cape Town.

Figure 1. Proportion of males searching since end of schooling
- African (dashed) and Coloured (solid)

3.2 Work Patterns in the School to Work Transition

Looking at the trends in search activity does not clarify whether joblessness decreases over time or whether discouragement increases. However, this question can be answered directly by looking at the employment trends garnered from the CAPS calendar. Figure 2 shows that there is a positive relationship between length of time since leaving school and proportion of the sample employed amongst African and Coloured males. The rate of employment acquisition seems to be higher prior to about 18 months after school as it decreases slightly after that. Furthermore, the racial differences are particularly striking. Six months after leaving school, 20% of Africans are working compared to 35% of Coloured males. These figures increase to 32% and 48% respectively after a year since leaving school and 50% and 65% respectively after three years. A similar trend is observed amongst females although the increase in proportion employed occurs at a slightly slower pace amongst the females. Also amongst females, the gap between the races increases significantly after about a year since ending school.

**Figure 2. Proportion of males working since end of schooling
– African (dashed) and Coloured (solid)**
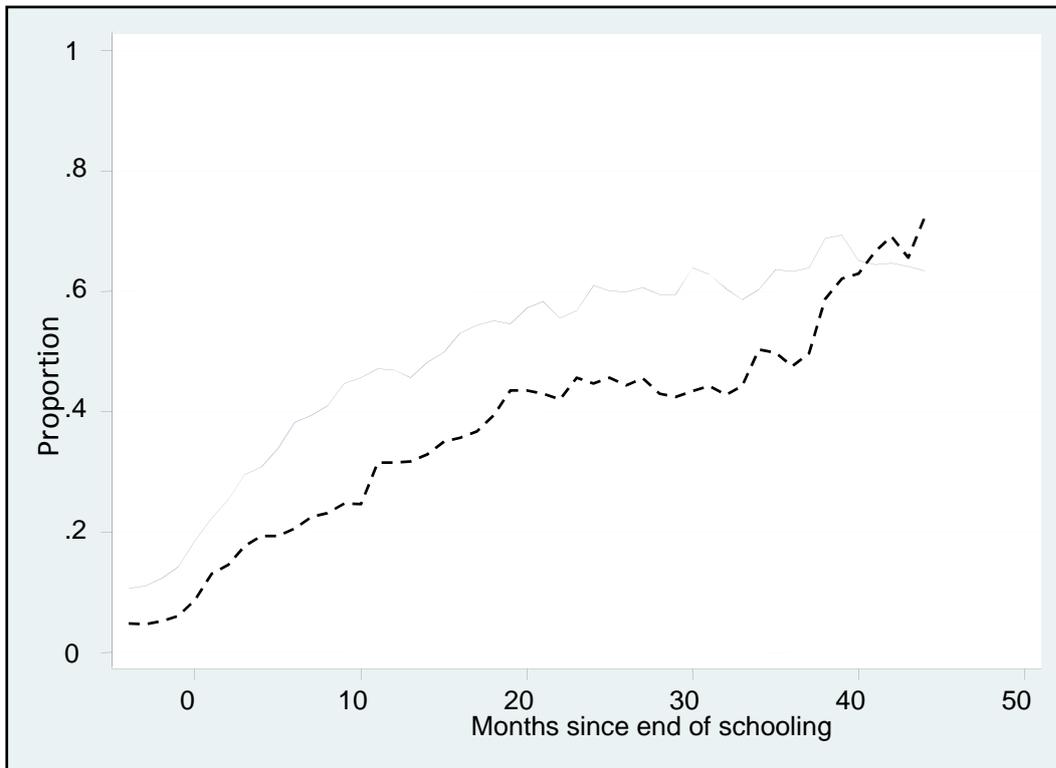
3.3 The Role of Education in the Work Patterns of Youth

It is clear that in the Cape Town labour market, the outcomes of Coloured youth are better than those of African youth, however, a question that naturally arises is whether education mitigates the observed racial disparities. Figure 3 displays the proportion of males with grade 12 and higher qualification who are working, by race. Evident from this diagram is that racial differences in employment are present even after the milestone of complete secondary education (matric) is reached by the youth in Cape Town.

Another way to tease out the education, work and race dynamics is to compare the employment outcomes of African youth with grade 12 to those of Coloured youth with less than grade 12 qualification as shown in Figure 4. The rationale here is that in so doing one can get a sense of the persistence of the labour market advantage of Coloured youth. Indeed, a higher proportion of Coloured males with less than grade 12 qualifications find jobs up to 22 months after leaving school after which African youth with matric catch up.

Figure 3. Proportion of African and Coloured males with grade 12 or more, working since end of schooling - African (dashed) and Coloured (solid)
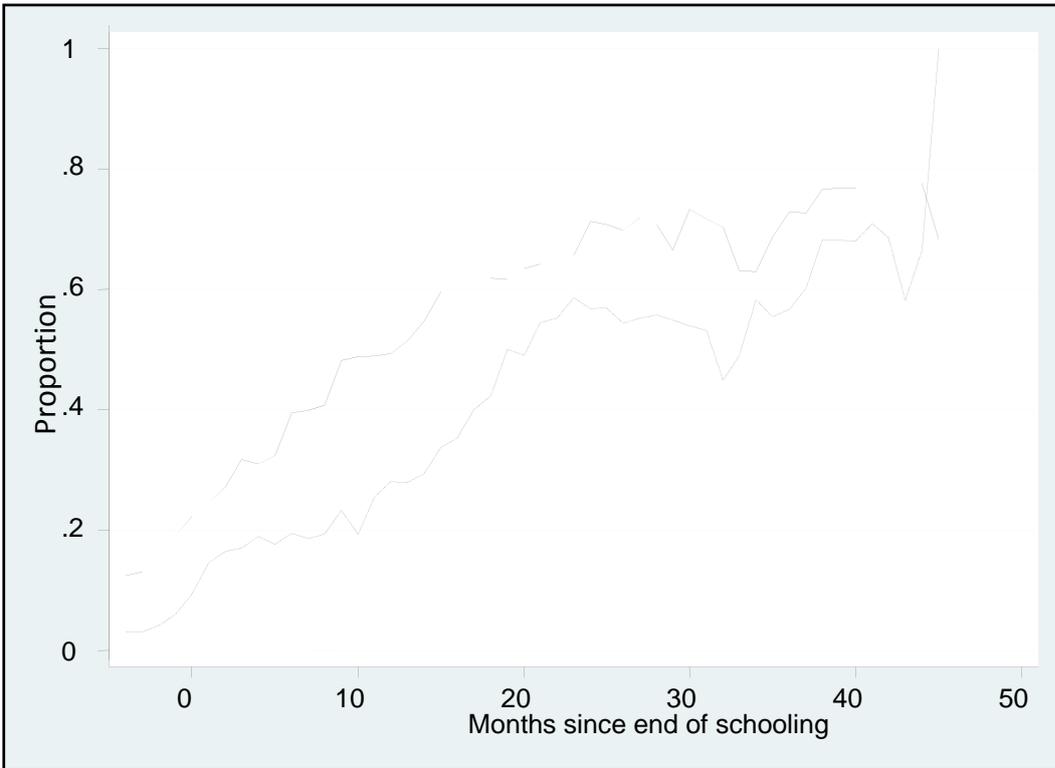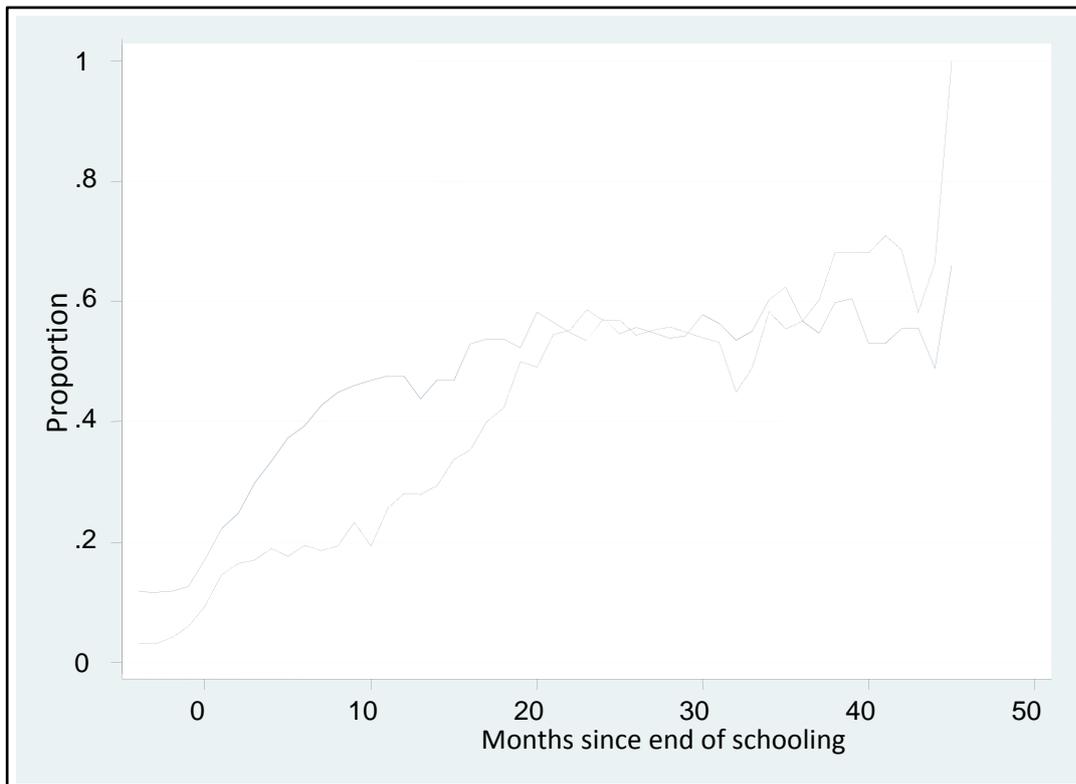

Figure 4. Proportion of African males with grade 12 or more (dashed) and Coloured males with grade 8 to 11 (solid) working since end of schooling

3.4 Gender and Employment Trends

Lastly, attention is shifted to differences in employment outcomes by gender. Figure 5 indicates that amongst African youth with grade 12 qualifications and higher, a higher proportion of males are employed throughout the months since leaving school. The difference in proportions of youth employed by gender actually widens after about 12 months since leaving schooling. Amongst Coloured youth the gender outcomes are much closer although the outcomes of males are still generally better than those of females. Figure 6 takes this analysis further by comparing Coloured females with matric and Coloured males with less than matric qualifications. It is only after two years after leaving school that the benefits of having grade 12 qualifications exceed those of being male.

Figure 5. Proportion of African males (dashed) and African females (solid) with grade 12 working since end of schooling
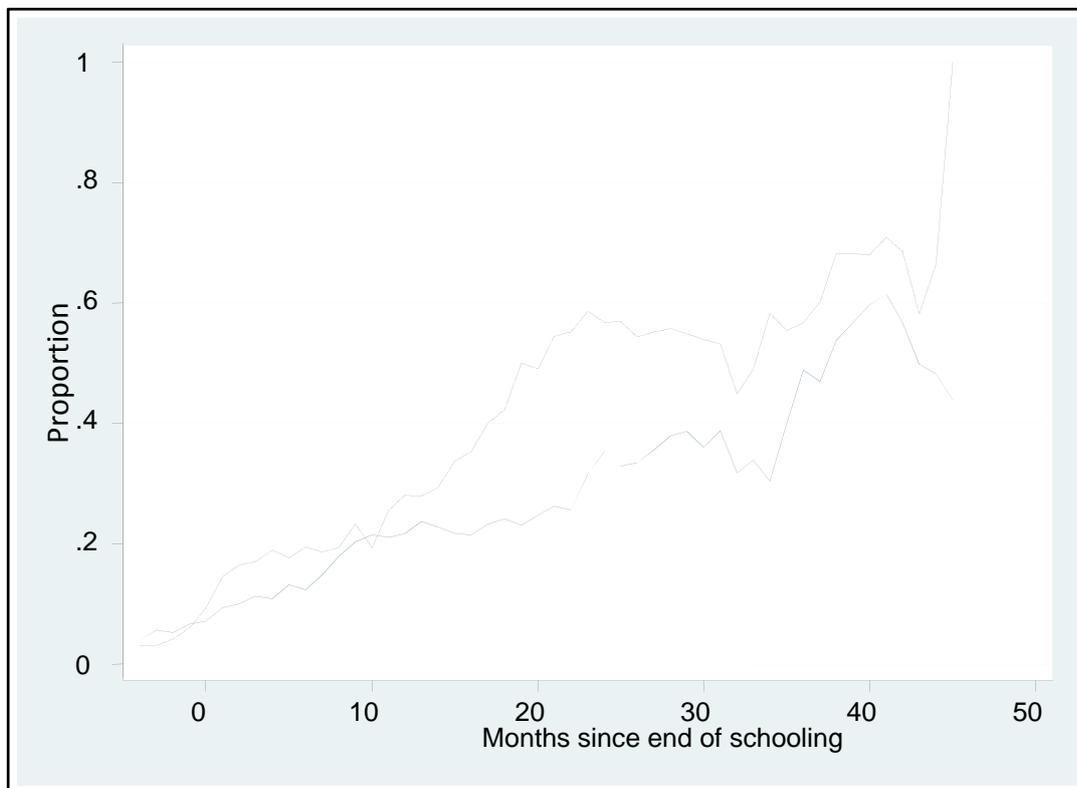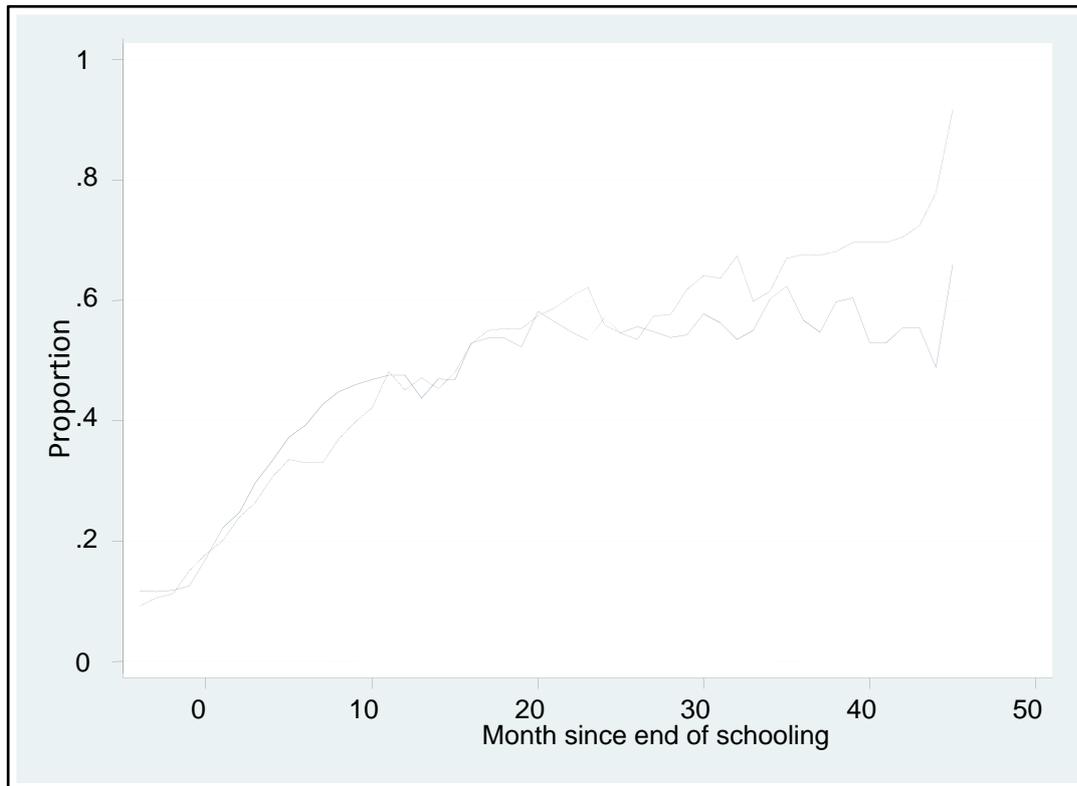
Figure 6. Proportion of Coloured females with grade 12 (dashed) and Coloured males with grade 8 to 11 (solid) working since end of schooling

This descriptive analysis has revealed that search activity by African and Coloured youth is rather similar but that there are greater differences in work outcomes in the months after leaving school. No more than 25% of youth of either race or gender search for work in any given month after leaving school. Coloured youth find jobs at a faster pace than African youth and this gap is wider amongst females although a lower proportion of females than males are working each month after school. The persistence of the better outcomes for Coloured youth is evident from the fact that Coloured males without matric qualifications do better than African males who have matric over the first 22 months after leaving school. The gender effect is also persistent in that Coloured females with grade 12 qualifications do not fair better than Coloured males with less than grade 12 qualification for up to about two years after schooling.

4. Duration analysis

4.1 Data and Methodology

Having analysed the general trends in job search and work activity after leaving school amongst youth in Cape Town, this section looks at the duration dependence of unemployed youth using survival analysis. The models that will be considered are hazard-based models as they are appropriate for situations where the focus is an end of duration occurrence, in this case the end of an unemployment spell. The hazard is therefore the exit rate from unemployment. Ordinarily survival data is censored but this is a feature that duration models can cope with. The data in this analysis is right censored. The analysis will begin with non-parametric estimation as this gives a clear summary of the data and it does not require any assumptions to be made about the functional form of the hazard. However, non-parametric analysis is limited by the fact that it does not allow for modelling of the effects of covariates on the hazard. Parametric analysis is necessary for this and it is conducted later in the chapter, after the preliminary non-parametric and semi-parametric analysis is carried out.

4.1.1 The Hazard Rate

To begin, it is useful to discuss the main concepts and notation relevant for the analysis carried out in this section. If T represents survival time, then T is regarded as a random variable with cumulative distribution function,

$P(t) = \Pr(T \leq t)$ and probability density function $p(t) = dP(t)/dt$.

The survival function $S(t)$ is the complement of the distribution function,

$S(t) = \Pr(T > t) = 1 - P(t)$.

Modelling of survival data often employs a hazard function, as is the case in this chapter. The hazard rate is defined as:

$$h(t/x) = \lim_{dt \to 0} \frac{P(t \leq T < t + dt \mid T \geq t, x)}{dt}$$

where, in the case of the labour market analysis carried out here, T is the duration of an unemployment spell and x is a vector of observed explanatory variables. The hazard rate is the probability that an individual will make a transition out of unemployment in the interval [$t, t+dt$], conditional on being unemployed at t (Cleves et al., 2004). More specifically, the hazard rate is the probability that a certain event will occur i.e. a transition into employment, given that the event has not yet occurred. Duration dependence is observed if the value of the hazard rate $h(t/x)$ changes over time t. Positive duration dependence occurs when the hazard function or the exit rate increases with time, whilst negative duration dependence occurs when the hazard function decreases with time.

4.1.2 The Explanatory Variables

The predictor variables chosen for this analysis are gender, race, age, education and the combined numeracy and literacy scores. It is expected that gender, race and education will have a positive effect on exiting unemployment. We have chosen to categorise education into complete secondary education or higher, and incomplete secondary education. In addition, incomplete secondary education has been further split into grade 10 or grade 11 to see whether being close to finishing secondary education has any advantage over dropping out earlier. Furthermore, the results of the literacy and numeracy test scores have been included as a measure of productive ability useful to securing employment. Preliminary investigation of the data has led to the inclusion of a race and education interaction variable. The inclusion of search strategy variables was considered and investigated but these variables created too much noise and were not in any way useful to the analysis.

4.2 Non-Parametric Analysis

In order to gain insight into the shape of the survival function the analysis begins with a univariate analysis before moving onto the more complex modelling. To start, Kaplan-Meier curves were plotted for most of the categorical predictors, only one is reflected below. The Kaplan Meier function is a non-parametric estimate of the survivor function s(t), or the probability of survival beyond time t. The survival function starts with 100% of the respondents unemployed (at analysis time zero), and drops towards zero as respondents make the transition to employment. Whenever a failure occurs, the survival curve drops to a new level, and to accommodate this, it is plotted as a step function. Log rank tests were conducted for the Kaplan-Meier plots and they indicted all these estimates to be statistically significant.

As an example, Figure 7 indicates that around 50% of the sample move out of a state of unemployment into a state of employment at about 12 months. Other plots, not reflected here, indicated that Coloured youth leave unemployment at a faster rate than for African youth. Fifty percent of Coloured youth have had their first job by 10 months after school whereas African youth reach this point after 20 months since leaving school. At 10 months after leaving school, only 25% of Africans have had their first job. Furthermore, it was found that the hazard of failure (that is finding employment) for males exceeds that of females. Roughly 50% of males have had a job by 12 months after leaving school whereas females reach this point only at 16 months after leaving school. Education also influences the hazard of leaving unemployment, where individuals with less than grade 12 level of schooling take slightly longer to find their first jobs when compared with those with more than grade 12.

Figure 7. Kaplan-Meier function
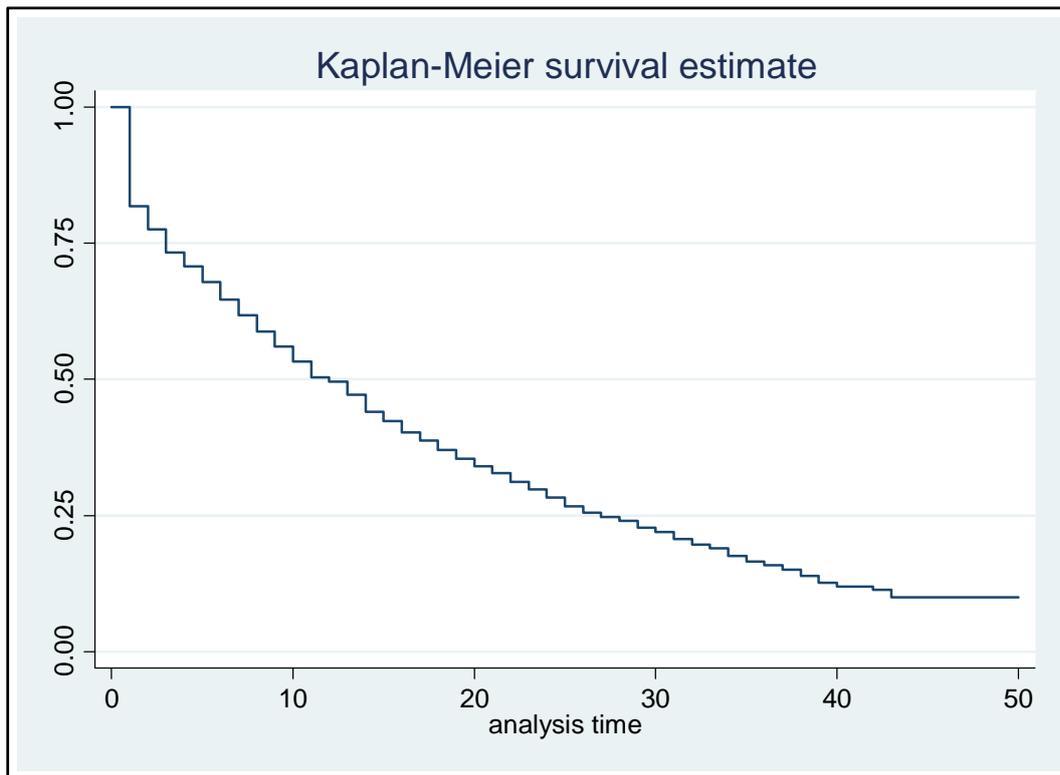
Source: CAPS own calculations

While the Kaplan-Meier estimates provide an indication of the general shape of the hazard as well as an estimate of the probability of survival beyond months after schooling, a more precise estimate of the effects of the variables discussed above on the hazard is obtainable from regression analysis, where covariates are controlled for. This will be discussed in more detail in the next section.

There are various estimators that can be used in survival analysis, however, the Weibull parametric estimator is the most commonly used in relation to labour market analysis. It is therefore desirable to use it in this analysis for the sake of comparisons with other studies. However, the appropriateness of the use of the Weibull estimator depends on whether the data used in this analysis satisfies the assumptions that need to be made when using it. Specifically, the main assumption is that of a proportional hazard (PH) where the effects of covariates do not change the shape of the hazard but influence just its position instead, as described below. The next section then begins with a detailed test of the data in order to confirm that the PH assumption holds.

4.3 Semi-Parametric Analysis

4.3.1 The Proportionality Assumption
The proportionality assumption states that differences in the explanatory variables imply proportional differences in the hazard at each survival time *t*. It specifies the effect of external covariates to be multiplicative on an underlying hazard function. In the

proportional hazards (PH) model, the effect of external covariates is to shift the entire hazard function profile up or down; the hazard function profile itself remains the same for every individual. The implication is that a matric qualification, for example, has the same impact on the hazard after any number of years of unemployment as it did after one year. Serneels (2002a) argues that youth living in households with low levels of welfare will have high discount rates and will (by virtue of being young) exhibit myopic behaviour, both conditions that support the proportionality assumption.

To begin, a Cox proportional hazards model is estimated, Table 2, and the analysis proceeds to test the validity of the proportionality assumption, Table 3. An advantage of the Cox proportional hazard model, often classified as semi-parametric, is that one can leave the baseline hazard unparamatised, that is, one need not make an assumption about the shape of the hazard over time. The Cox proportional hazards model will not be an end in itself in this analysis as the goal is to obtain an estimate of the hazard distribution while the Cox model only estimates the covariate effects. It is established below that the proportionality assumption has not been violated and the analysis then proceeds with the use of the Weibull parametric estimator.

Survival analysis typically examines the relationship of the survival distribution to covariates. Most commonly, this examination entails the specification of a linear-like model for the log hazard. For example, a parametric model based on the exponential distribution may be written as,

$$h_i(t) = \exp(\alpha + \beta 1 x_{i1} + \beta_2 x_{ik} + \ldots\ldots + \beta_k x_{ik})$$

or equivalently,

$$\log h_i(t) = \alpha + \beta 1 x_{i1} + \beta_2 x_{ik} + \ldots\ldots + \beta_k x_{ik}$$

where log is the natural log.

In this case, i is a subscript for observation, and the x's are the covariates. The constant α in this model represents a log-baseline hazard, since $\log h_i(t) = \alpha$ [or alternatively, $h_i(t) = e^{\alpha}$] when all of the x's are zero. As mentioned above, the Cox model in contrast, leaves the baseline hazard function $\alpha(t) = \log h_0(t)$ unspecified:

$$\log h_i(t) = \alpha(t) + \beta 1 x_{i1} + \beta_2 x_{ik} + \ldots\ldots + \beta_k x_{ik}$$

Table 2. Cox proportional Hazards Regression

Male	1.343***
	[0.093]
African	0.534***
	[0.053]
Age	2.124***
	[0.590]
AgeSquared	0.982**
	[0.008]
Grade 10 to 11	1.129
	[0.115]
Grade 12plus	1.287**
	[0.152]
Matric African	0.860
	[0.112]
Lit-num test scores	1.022
	[0.053]
Observations	19726

Robust standard errors in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%
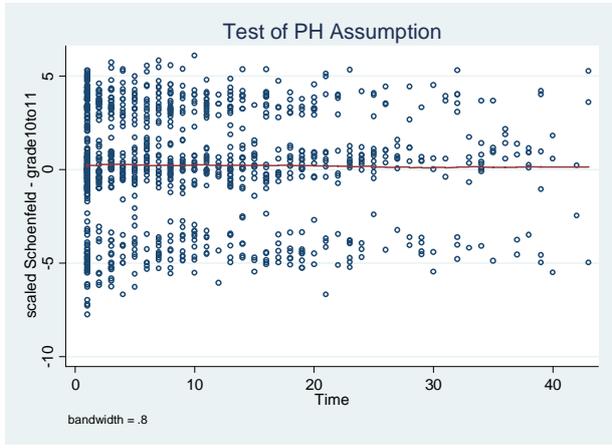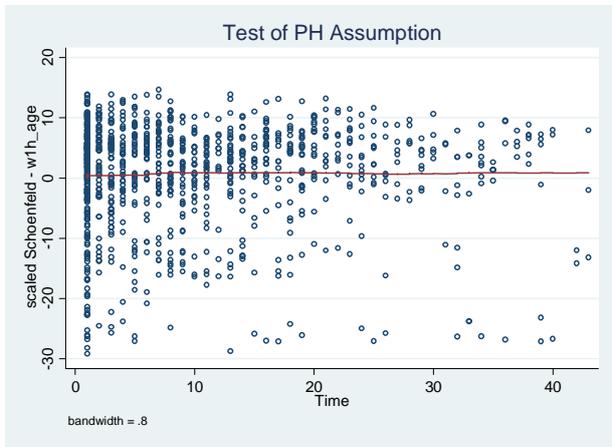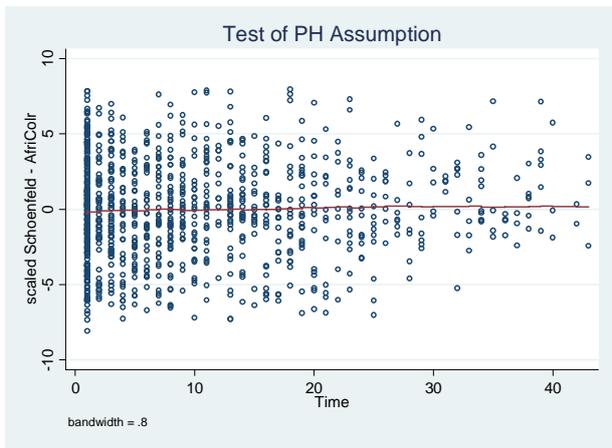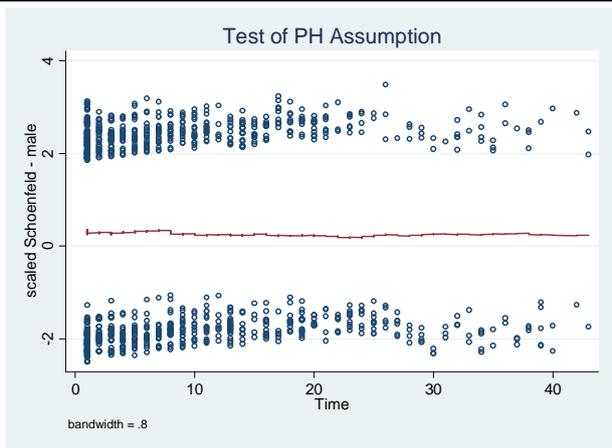
Source: CAPS own calculations

One empirical test of whether the proportional hazards assumption holds is through an analysis of the Schoenfeld residuals derived from the Cox proportional hazards regression. After estimating both the Schoenfeld and scaled Schoenfeld residuals, and performing the variable-by-variable test, it emerges that there is no evidence to indicate that the proportional hazards assumption has been violated. The results of the global test and the variable-by-variable test are displayed in Table 3 and they indicate that the proportionality assumption has not been violated.

Table 3. Test of Proportional-Hazards Assumption

	rho	chi2	df	Prob>chi2
Male	-0.02912	0.83	1	0.3622
African	0.02854	0.87	1	0.3514
Age	0.04173	1.71	1	0.1916
AgeSquared	-0.03974	1.56	1	0.2112
Grade10to11	-0.00193	0.00	1	0.9541
Grade12plus	0.01292	0.15	1	0.7014
MatricAfrican	0.01055	0.12	1	0.7309
Lit-num test scores	-0.02184	0.35	1	0.5553
Global test		13.42	8	0.0981

Source: CAPS own calculations

The Schoenfeld residuals are based on the contributions of each of the predictor variables to the log partial likelihood. In theory, the scaled Schoenfeld residuals are Schoenfeld residuals adjusted by the inverse of the covariance matrix of the Schoenfeld residuals. Under the assumption that the distribution of the predictor variables is similar in the various risk sets, the adjustment can be performed using the variance-covariance matrix of the parameter estimates divided by the number of events in the sample. The null hypothesis for the test on proportional hazards based on the scaled Schoenfeld residuals is that the slope of Schoenfeld residuals against a function of time is zero for each predictor variable. Plots of the scaled Schoenfeld residuals should reveal a horizontal line if the proportionality assumption holds. Indeed, it is evident from Figure 8 that the plots of the scaled Schoenfeld residuals of all of the predictors indicate that the proportionality assumption has not been violated.

Test of PH Assumption (scaled Schoenfeld - male), bandwidth = .8

Test of PH Assumption (scaled Schoenfeld - AfriColr), bandwidth = .8

Test of PH Assumption (scaled Schoenfeld - w1h_age), bandwidth = .8

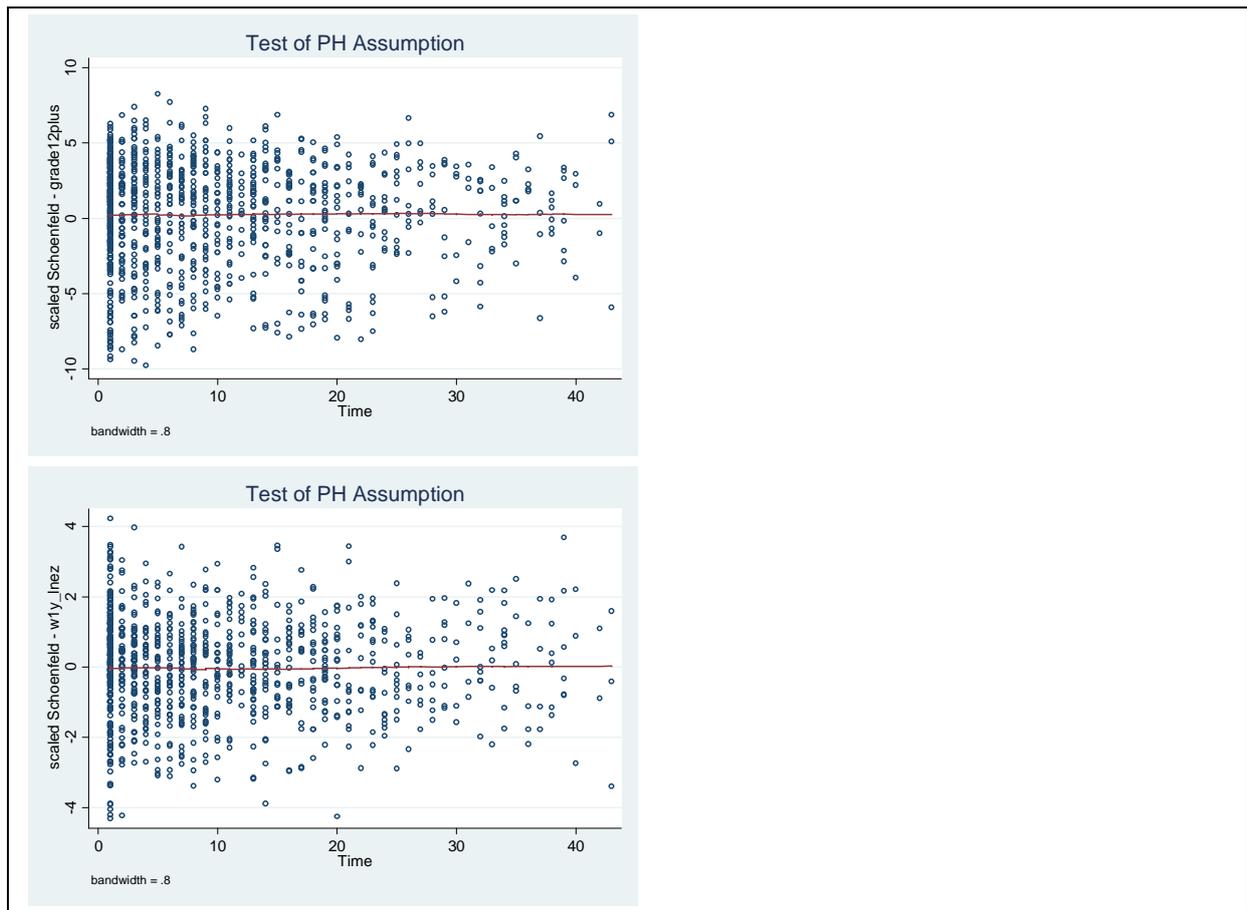Test of PH Assumption (scaled Schoenfeld - grade10to11), bandwidth = .8

Figure 8. Plots of Schoenfeld residuals as a test of the PH assumption

Source: CAPS own calculations

4.4 Parametric Analysis

4.4.1 Weibull Regression Analysis

As discussed earlier, the non-parametric analysis carried out above is limited by the fact that it does not allow for modelling of the effects of covariates on the hazard. Parametric proportional hazards models on the other hand allow such modelling but they require that the shape of the baseline be specified. Possible specifications of the baseline hazard are Exponential, Generalised gamma, Gompertz, Log-logistic, Log-normal, and Weibull. Weibull hazard models have been used to analyse a wide variety of issues in economics, including duration of unemployment, duration of labour strikes, duration of litigation in legal disputes, and even traffic congestion. They have also been widely used to model duration dependence in OECD countries. The Weibull specification is popular because of its relative flexibility and simplicity. Indeed, using the Weibull baseline hazard is the only circumstance under which the model satisfies both the proportional hazards, and accelerated failure time models. The Weibull is also the simplest parametric form that directly estimates duration dependence.

Having confirmed above that the proportionality assumption has not been violated, the Weibull proportional hazards model has been chosen to model unemployment duration in the analysis that follows.

The baseline hazard, $h_0(t)$, is specified as

$$h_0(t) = pt^{p-1}.$$

Thus the hazard is defined as

$$h(t \mid X_j) = h_0(t)\exp(X_j\beta_x)$$
$$= pt^{p-1}\exp(X_j\beta_x)$$

The shape parameter, p, provides information about the shape of the hazard function and indicates the direction of duration dependence. If $p > 1$, the hazard is monotonically rising with time, indicating positive duration dependence; conversely if $p < 1$, the hazard is monotonically falling with time, thereby indicating negative duration dependence. Finally, if $p = 1$, the hazard is flat, thus implying an exponential distribution and no duration dependence (Cleves et al., 2004).

An important issue in survival analysis is the distinction between duration dependence of the hazard rate and unobserved heterogeneity (Jenkins, 2004). Unobserved heterogeneity may occur because of omitted variables and/or measurement errors. If unobserved heterogeneity is ignored, there is a tendency for the duration dependence estimate to be biased downwards (Heckman & Singer, 1984). Specifically, failure to incorporate heterogeneity appears to lead to a downward biased estimate of duration dependence and a bias toward zero for the effect of external covariates. For example, assume that a group of individuals with differing personal characteristics are in the preliminary stages of an unemployment spell. Those individuals who possess the characteristics most favoured by employers will leave unemployment in the early stages of the unemployment spell, leaving behind those with less favourable characteristics and lower employment prospects. Thus, it would appear that exit probabilities are negatively related to unemployment duration, and that hazard rates decline throughout the unemployment spell. However, this effect actually "represents changes in the distribution of unobserved characteristics in the population yet to exit from unemployment", and does not exhibit true duration dependence (Kalb 2001).

The heterogeneity term has a multiplicative effect in the hazard. In this case, the hazard is defined as

$$h(t / X_j, \alpha_j) = \alpha_j h(t / X_j)$$

where α_j represents an unobserved heterogeneity term indicating that "individuals in the population are heterogeneous due to factors that remain unobserved" (Cleves et al., 2004, p.279).

In order to estimate the unconditional hazard function, whereby the hazard is not conditional on the value of α_j, the unobservable heterogeneity term is integrated out of the hazard function (Cleves et al., 2004). In order to integrate out α_j, a distribution for the unobserved heterogeneity term must be specified. (Cleves et al., 2004). The inverse Gaussian distribution has been chosen here to control for unobserved heterogeneity. Furthermore, sampling weights have been used and standard errors have been adjusted for clustering.

Table 4. Weibull Proportional Hazards Regression

Male	1.780***
	[0.227]
African	0.323***
	[0.059]
Age	3.351**
	[1.720]
AgeSquared	0.972**
	[0.014]
Grade10to11	1.234
	[0.229]
Grade12plus	1.614**
	[0.348]
MatricAfrican	0.753
	[0.182]
Lit-num test scores	1.058
	[0.101]
/ln_p	0.500***
	[0.037]
P	1.649***
	[0.061]
Theta	15.695***
	[2.980]
Observations	19726

Robust standard errors in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%
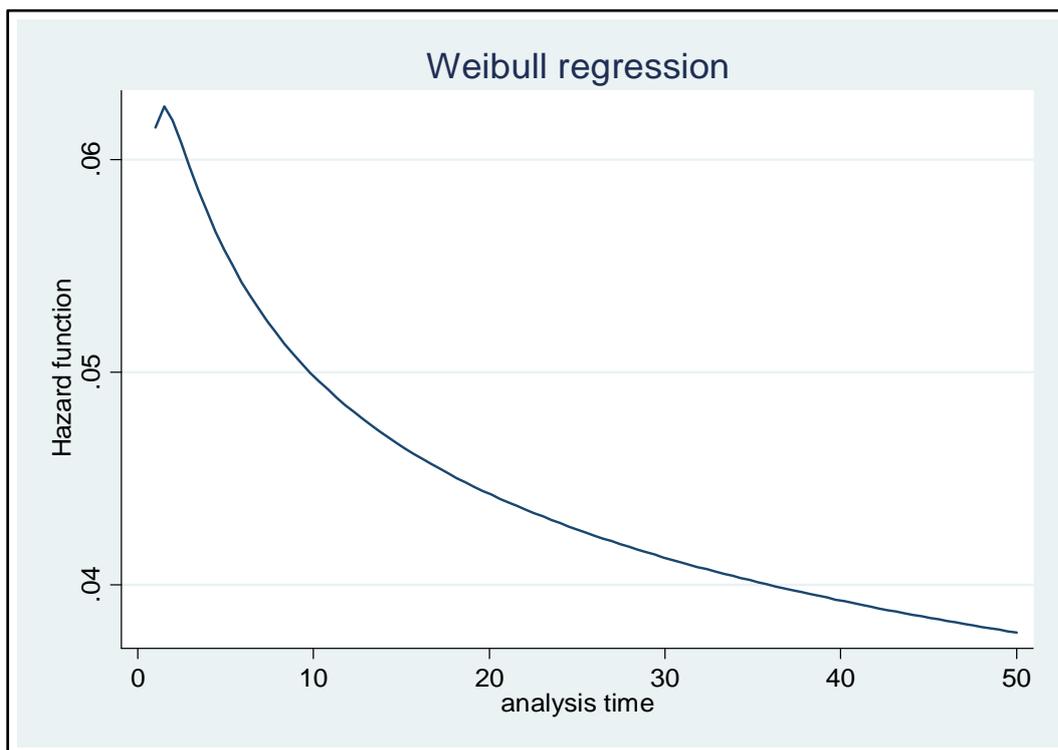Source: CAPS own calculations

The statistic for the shape parameter, p, is the same as α in the model specification above. The /ln_p statistic is the estimate derived from maximum likelihood estimation and p = exp(/ln_p). The p statistic being greater than 1 in the Weibull regression output, suggests that the hazard is monotonically increasing. The test of the null hypothesis that the log of p is equal to zero (which is equivalent to testing for p = 1) is clearly rejected. This result implies positive duration dependence, which means that the longer youth are in a state of unemployment, the more likely they are to exit unemployment and find employment. The regression results suggest that race and gender have a highly significant effect on the duration of unemployment. Being African reduces the hazard of moving into a state of

employment by close to 70%. In terms of gender, being a male youth increases the hazard of exiting unemployment by 78%. Each year in age increases the hazard by more than 100%, significant at the 10% level of significance however. The reported hazard ratio for the age-squared variable suggests that the positive effect of age on the hazard decreases beyond a certain age.

The effect of education is interesting as it suggests that almost completing secondary schooling (achieving grade 10 or grade 11) does not have a significantly different effect on the hazard than attaining less than grade 10. However, achieving secondary schooling or higher increases the hazard of exiting unemployment by 61%, holding other factors constant. The race and education interaction variable does not have a significant effect on the hazard. The insignificant effect of the interaction variable is surprising given the background of the findings earlier in this paper, that African youth with matric have less favourable outcomes than Coloured youth without matric. The direction of the estimated effect is as expected though. Similarly literacy and numeracy test scores do not impact significantly on the hazard of exiting unemployment although the positive effect is as expected.

Figure 9. Hazard function

Source: CAPS own calculations

The Weibull hazard function plotted in Figure 9 is derived from the Weibull regression that was run earlier and it reflects the percentage of unemployed youth who make the transition into employment each month. The function reaches a peak at just above 6%. This peak is reached at between zero and six months after entering the labour market. For the ensuing months more youth move into employment.

More detail is obtained by looking at the hazard function by race and education, as in Figure 10. Figure 10 plots the hazard function for Africans and Coloureds with and without matric, based on the Weibull regression. The beneficial effects of having more education are evident within race, in that Africans who possess matric find jobs at a faster rate than Africans without matric and similarly for Coloureds with matric compared to Coloureds without matric. What is striking though about the functions reflected in Figure 10 is that Coloured youth who do not have matric have a higher hazard rate than African youth with matric.

Figure 10. Hazard function by race and education
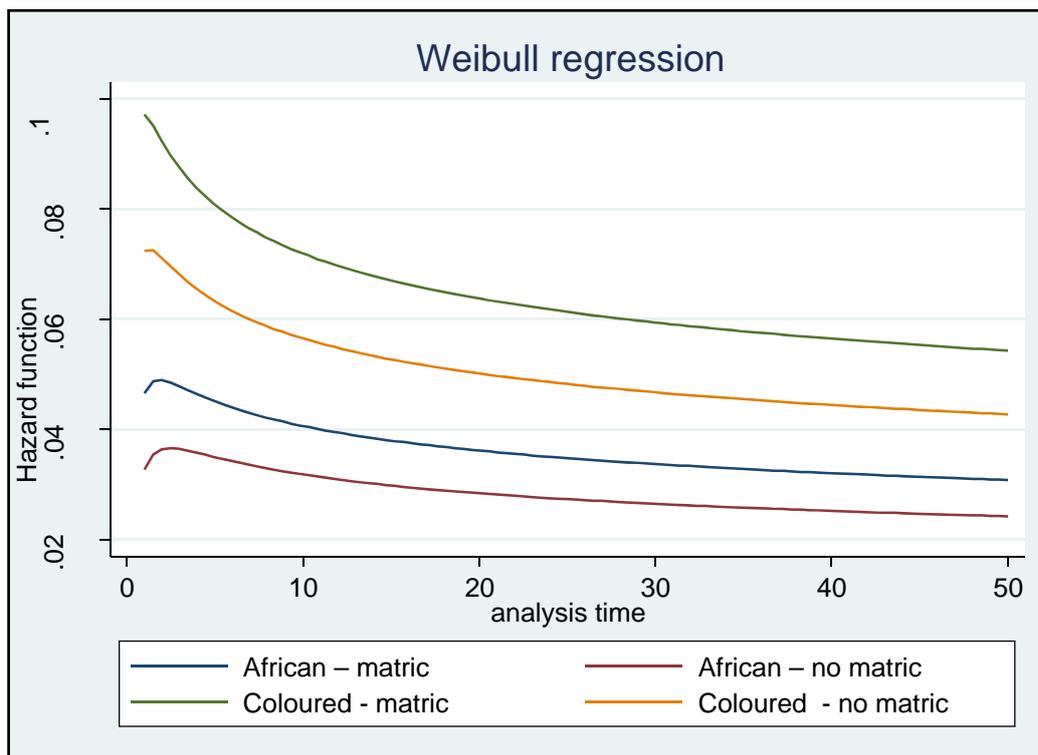
Source: CAPS own calculations

The survival function in Figure 11 depicts the same pattern as above but from a different perspective. It begins with 100% of individuals unemployed at the time of entering the labour market. The survival function then reflects the percentage that is still unemployed for each month that youth are in the labour market. As above, the plots contrast race and education once more. The higher the position of the survival function of one group relative to another, the slower the progression of that group from unemployment to employment. The effect of education is apparent once more as reflected in Figure 11. Within each race, fewer individuals with matric survive in the state of unemployment relative to individuals without matric. Furthermore, the survival functions of Coloured youth lie below those of African youth regardless of educational attainment, suggesting that race overrides education in determining progression to employment.

Figure 11. Survival function
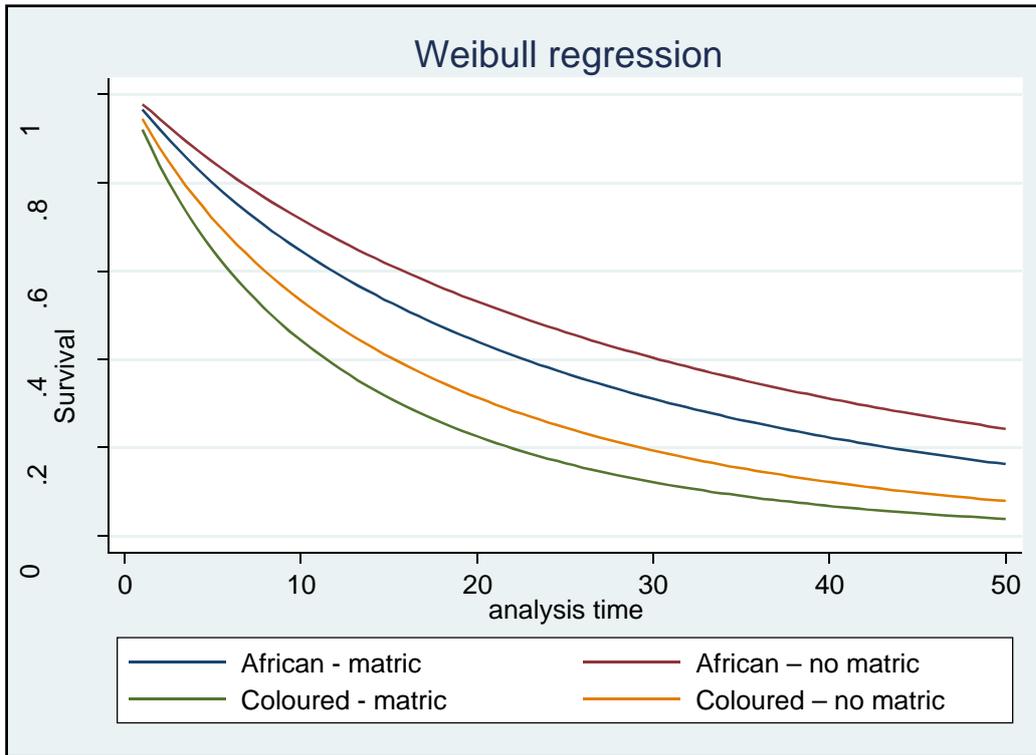
Source: CAPS own calculations

Figure 12 provides an education-and-gender based depiction of the hazard function. The group with the highest percentage of individuals exiting unemployment is males with matric, while the slowest exit rate is by women without matric. Similar to the relationship between education and race analysed above, Figure 12 indicates a clear male advantage that overrides the benefit of educational attainment. Males who do not possess matric have slightly higher hazard rates than females with at least matric level of educational attainment.

Figure 12. Hazard function by gender and education
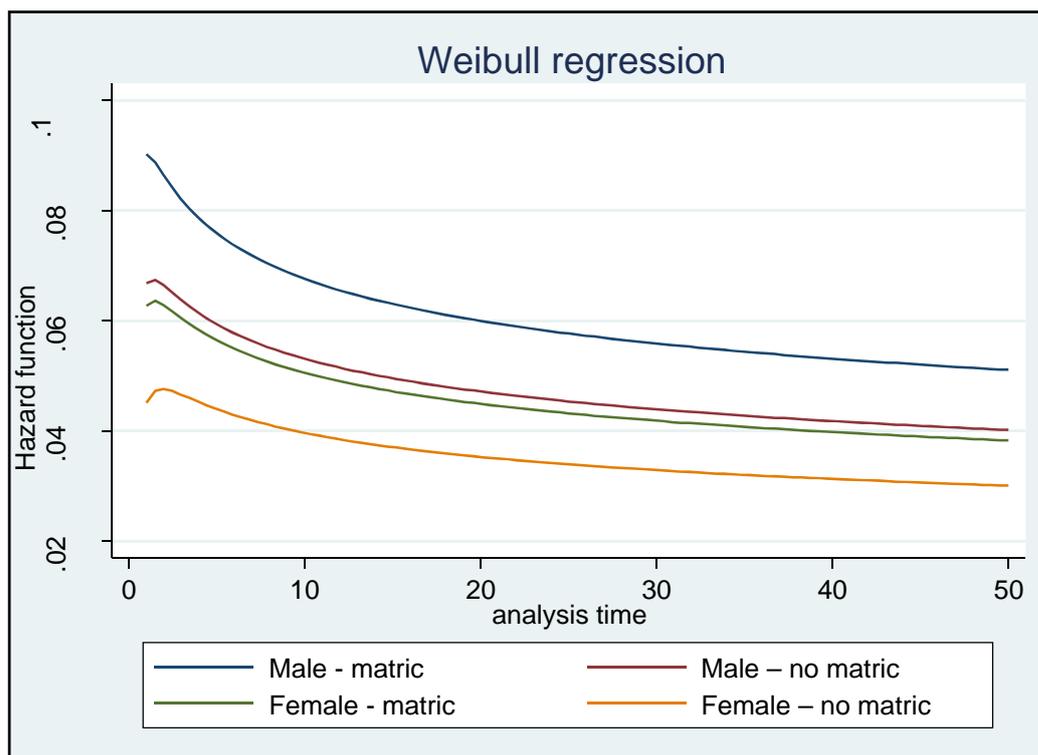
Source: CAPS own calculations

5. Conclusion

The discussion in this chapter has highlighted a number of interesting features of the labour market in Cape Town. First, the demography of Cape Town differs from that of other areas of South Africa, rural or urban. Africans dominate in numbers in other regions of South Africa but in Cape Town around half the population comprises Coloureds, followed by Africans at around 35% and then Whites at around 14%. Employment prospects for youth appear to be higher in Cape Town than the rest of South Africa as the 2001 Census 10% Microsample data indicates that 19% of 15 to 22 year old youth are employed in Cape Town compared to 10% for the rest of South Africa. The proportion of youth who are unemployed is similar to the rest of South Africa though. With the proportion of White youth unemployed being only 4% it is clear that the unemployment in Cape Town is mainly driven by African and Coloured youth. However, African youth appear to be hardest hit with only 10% of them employed compared to 23% of Coloured youth. This implication was tested formally with an analysis that utilised non-parametric, semi-parametric and parametric tools.

The findings are that race and gender effects are evident with regard to labour market outcomes in the Cape Town. Job search patterns and proportions by race are very similar between African and Coloured youth, however, that similarity does not translate into similar employment outcomes. Coloured youth exit schooling far quicker than African youth and this could be because of the higher opportunity cost of remaining in school given relatively

favourable employment prospects. The transition rate from school to work happens at a slower rate for Africans. Africans tend to move from schooling to a long period of unemployment while Coloureds make a smoother transition to work. Females within each race have more schooling than males, however, the employment outcomes do not reflect this. The descriptive analysis and the regression analysis confirm that race has a big influence on labour market outcomes, with Coloured youth without matric having greater success at finding employment than African youth with Matric. It seems that Coloured males have a dominant advantage within the labour market in Cape Town because Coloured females with matric have worse employment outcomes than males without matric for about two years after leaving school. The effect of education within race, however, is consistent with our expectations.

The nature of duration dependence was analysed for the youth labour market in Cape Town. Before adopting the Weibull parametric estimator for the analysis, a detailed test of the applicability of the proportional hazard assumption was carried out. A Weibull model was then set up as a result. The results confirm that Coloured youth have a clear labour market advantage over African youth in Cape Town. This advantage probably stems from network effects that are likely more effective among Coloured youth. In addition to this, the legacy of past job reservation policies may feed into these network effects. Indeed, historically the Coloured race received higher expenditures on schooling, fewer restrictions on residential mobility and better access to jobs relative to the African race.

Furthermore, the analysis in this chapter also reflects that males, older youth and youth who have completed secondary schooling enjoy relatively good labour market outcomes. Parametric analysis revealed positive duration dependence in the Cape Town labour market, meaning that the longer an individual is in a state of unemployment, the greater the likelihood of moving out of it and into a state of employment. This result bodes well for youth in that it implies a queuing effect in the labour market and that youth will ultimately find jobs. Indeed, the findings of labour market advantage of even 25-30 year old youth compared to 15 to 24-year-old youth support the notion of a job queue. Positive duration dependence is not a given in all labour markets, however. In fact economic theorising suggests that duration dependence should ordinarily be negative, as the longer one is in state of unemployment the more one loses touch with the labour market and experiences erosion of human capital, factors which make one less attractive to employers. Fortunately these dynamics do not seem to be binding in the labour market in Cape Town and probably in the rest of South Africa, given the relative employments outcomes of adults and youth.
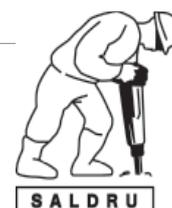
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southern africa labour and development research unit

The Southern Africa Labour and Development Research Unit (SALDRU) conducts research directed at improving the well-being of South Africa's poor. It was established in 1975. Over the next two decades the unit's research played a central role in documenting the human costs of apartheid. Key projects from this period included the Farm Labour Conference (1976), the Economics of Health Care Conference (1978), and the Second Carnegie Enquiry into Poverty and Development in South Africa (1983-86). At the urging of the African National Congress, from 1992-1994 SALDRU and the World Bank coordinated the Project for Statistics on Living Standards and Development (PSLSD). This project provide baseline data for the implementation of post-apartheid socio-economic policies through South Africa's first non-racial national sample survey.

In the post-apartheid period, SALDRU has continued to gather data and conduct research directed at informing and assessing anti-poverty policy. In line with its historical contribution, SALDRU's researchers continue to conduct research detailing changing patterns of well-being in South Africa and assessing the impact of government policy on the poor. Current research work falls into the following research themes: post-apartheid poverty; employment and migration dynamics; family support structures in an era of rapid social change; public works and public infrastructure programmes, financial strategies of the poor; common property resources and the poor. Key survey projects include the Langeberg Integrated Family Survey (1999), the Khayelitsha/Mitchell's Plain Survey (2000), the ongoing Cape Area Panel Study (2001-) and the Financial Diaries Project.