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# Labour market turnovers among South African youths

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**Abstract**

We describe the labour market turnovers of young people using a household survey data collected from Cape Town industrial area. We measure the correlates of first unemployment duration out of school and find that matriculation and late cohort (leaving school after 2007) are related with reduced initial unemployment, yet matriculation impacts are reduced among late cohort relative to early cohort. Our estimation reveals that initial unemployment is not related with subsequent employment duration nor wage rates, but related with number of turnovers which suggests that a shorter spell is associated with more stable job tenure.

**Keywords:** youth unemployment, school-to-work transition, scarring effect
**JEL classification:** J13, J63, J64

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Labour market turnovers among South African youths

Rulof Burger[†], Seiro Ito[‡]

# I Introduction

It is well documented that the unemployment rates are high among South African youths. It can be argued that having the unemployed youths impede the economy to reach its full potential. Firstly, the idle resource under market imperfection is considered as inefficient. Secondly, the youths, defined as aged between 20 and 35 in this paper[*1], is a prime generation for learning-by-doing. If a youth remains unemployed for a prolonged period, he misses a productive window of trainability which may result in a long spell of unemployment or low wage employment. Thirdly, with limited accumulation of worker skills, the economy as a whole may experience a reduce rate of growth as suggested by the standard macroeconomic growth models. Fourthly, limited growth will have a natural consequence on inequality in an economy with limited achievements in promoting human capital accumulation among the low income population. A young economy in a dire need of reducing socioeconomic inequality will be forced to wait another few decades to see the economic prosperity trickling down.

In this regard, studies that have suggested the long spells of unemployment among South African youth are particularly alarming. While the mechanism behind unemployment is much debated and remains unsettled, there is a fairly wide consensus on its costs (Banerjee et al., 2008). Despite these alarming perceptions on youth unemployment, little is known about the dynamic consequences of unemployment especially during the period of school-to-work transition, namely the occurrence dependence and lagged duration dependence as defined by Heckman and Borjas (1980). The only exception to the best of author's knowledge is the work by Lam et al. (2008) who find, based on a representative sample of youths in the Greater Cape Town area, strong effects of schooling on subsequent employment during the first four years after leaving the school. Despite the dfferences in geographical scope and timing, we also find a strong correlation between receiving a matriculation diploma and employment.

The purpose of this paper is to show the correlation between multiple labour cycles (spells) in a descriptive way. We focus on the urban youth population near industrial areas where employment opportunities are relatively abundant. Their typical educational qualification is between a few years short of matriculation and matriculation which corresponds to the majority of youths in the country. The data we use is based on the recall information of a household survey we conducted in 2014-2015. We use parametric and semiparametric duration models to estimate the correlates of unemployment and employment spells. In light of unemployment scarring effects, we also investigate the association between the initial unemployment spell and subsequent employment characteristics.

Results show that matriculation and late cohorts are associated with shorter initial unemployment duration in their school-to-work transition. While the duration became shorter among the late cohort, the advantage of having matriculation had become smaller which may indicate the deterioration of diploma signals in the labour markets. We find a positive correlation between unemployment duration with the number of adult members in a household, which is consistent with the lack of job related network that prolongs the search, as larger households tend to be poorer. In examining the scarring effects, we find the duration of initial unemployment is not correlated with subsequent

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[*1] Following ILO conventions, Statistics South Africa uses the definition of 15-24 for the youth. We adopt older lower- and upperbounds to capture from our sampled respondents at least some experience in the labour markets. As will be shown, there are a number of 24 year olds who have never worked before, yet most of them seem to get some jobs around 30 years of age.

employment intensity. Our finding, under a limitation of a relatively short observation period of 5 years and a limited sample size, suggests that a difficulty or an ease in finding the first job may not be related to the subsequent job career. This is in contrast to the previous empirical literature from the developed economies that the nature of initial job out of school, or initial labour market environment in general, may have a strong influence on subsequent career paths(Oreopoulos et al., 2012; Adda et al., 2013; Giuliano and Spilimbergo, 2014; Cutler et al., 2015). We find that employment intensity is positively correlated with the number of matriculated adult members. This suggests the role of job related networks that matriculated adults may offer that results in employment security.

The rest of paper is organised as following. In the next section, we describe the data and its characteristics. In the third section, we analyse the first unemployment spells. We use parametric models hazard models. In the fourth section, we study the relationship between first unemployment spell and subsequent employment intensity. In the final section, we conclude. In the appendix, we report robustness checks and estimate semiparametric Cox proportional hazard models.

# II Data

We have chosen two urban townships near Cape Town. We have chosen the location strategically to be close to an industrial area so we can observe frequent turnovers.[*2] The selection of townships is purposeful to include one black community and one couloured community.

We have initially allocated about 400 respondents in both black and coloured communities. As the survey required a formal permission from each street committee in the black community while the coloured community did not require any, the final sample size was 427 in the coloured community and 242 in the black community. The respondents were chosen by stratified random sampling. Strata are street blocks and we have randomly chosen the houses in each block. In each house we visited, we sampled up to three youths aged 20-35.[*3] When there were more than three youths, we randomly chose the respondents by referring to a table of pre-randomised numbers.

## II.1 Information from roster

Based on the household roster information, Table 1 indicates that our households are comprised mostly of children (aged 0-15), youths (20-35), and adults (36-64). We see that the youths form the biggest age group in our sample despite their limited age range. This is not surprising as we have oversampled the youth by selecting the households with at least one youth. Our sample is representative of households with at least one youth in the respecitve communities.

[*2] One can easily walk to the industrial area from one of the sampled communities, and taking a minibus to other areas will cost around R10 (a little less than 1 US Dollar) for each way at the time of the survey. Our sample is geographically advantageous than the rest of South Africa in finding a job in the manufacturing sector and associated service industries.

[*3] The definition of youths used by the Statistics South Africa is 18-35. We opted to drop 18 and 19 year olds from our sample. This is because we need to observe the transition from school to work that may take a few years. In addition, it is questionable that this high teen population is a part of the labour force. Indeed, as we see later in Table 3, the rate of labour force participation is lower than the other age group.

TABLE 1 Composition of age groups

| age range | 0-15 | 16-19 | 20-35 | 36-64 | 65- | total |
|---|---|---|---|---|---|---|
| age group | child | minor | youth | adult | senior | |
| males | 0.156 | 0.024 | 0.169 | 0.108 | 0.013 | 0.470 |
| females | 0.119 | 0.024 | 0.197 | 0.156 | 0.033 | 0.530 |
| total number | 654 | 115 | 868 | 625 | 110 | 2372 |

Source: Survey data.

TABLE 2: Unemployment rates by age group among household members

| age range | 0-15 | 16-19 | 20-35 | 36-64 | 65- | total |
|---|---|---|---|---|---|---|
| age group | child | minor | youth | adult | senior | |
| males | 100.00 | 88.46 | 58.44 | 35.21 | 66.67 | 51.99 |
| females | 80.00 | 68.42 | 65.25 | 42.95 | 33.33 | 56.31 |
| total | 85.71 | 80.00 | 62.09 | 39.85 | 50.00 | 54.40 |

Source: Survey data.

Note: Unemployment rate is defined as a ratio of nonworking individuals who were ready to work to all individuals who were ready to work, all in the recall period of past 7 days. Nonworking is defined as working for a remuneratieve or nonremunerative job for at least one hour.

TABLE 3: UNEMPLOYMENT AND LABOUR FORCE PARTICIPATION RATES BY AGE GROUP AMONG HOUSEHOLD MEMBERS

| age range | 16-19 | 20-25 | 26-30 | 31-35 | total |
|---|---|---|---|---|---|
| males, with matric | (12) | (64) | (21) | (19) | (116) |
| unemployment rates (%) | 100.00 | 52.54 | 52.38 | 26.32 | 50.00 |
| OLF | [7] | [5] | [0] | [0] | [12] |
| males, no matric | (45) | (128) | (101) | (68) | (342) |
| unemployment rates (%) | 85.71 | 65.29 | 59.18 | 61.19 | 63.84 |
| OLF | [24] | [7] | [3] | [1] | [35] |
| females, with matric | (13) | (69) | (39) | (39) | (160) |
| unemployment rates (%) | 75.00 | 60.66 | 55.26 | 58.97 | 59.59 |
| OLF | [5] | [8] | [1] | [0] | [14] |
| females, no matric | (45) | (152) | (113) | (55) | (365) |
| unemployment rates (%) | 63.64 | 72.92 | 68.18 | 55.56 | 68.03 |
| OLF | [34] | [8] | [3] | [1] | [46] |

Source: Survey data.

Note: OLF = Out of labour force. Numbers in round brackets show the cell sample size among household members of survey respondents.

TABLE 4: Unemployment of respondents, by gender and education

| age range | 20-25 | 26-30 | 31-35 | total |
|---|---|---|---|---|
| males, with matric | (49) | (10) | (17) | (76) |
| unemployment rate (%) | 63.27 | 50.00 | 23.53 | 52.63 |
| males, no matric | (106) | (68) | (43) | (217) |
| unemployment rate (%) | 65.09 | 61.76 | 60.47 | 63.13 |
| females, with matric | (60) | (32) | (29) | (121) |
| unemployment rate (%) | 60.00 | 56.25 | 65.52 | 60.33 |
| females, no matric | (126) | (76) | (44) | (246) |
| unemployment rate (%) | 77.78 | 67.11 | 65.91 | 72.36 |
| males, no lag | (82) | (49) | (29) | (160) |
| unemployment rate (%) | 60.98 | 53.06 | 48.28 | 56.25 |
| males, behind | (73) | (29) | (31) | (133) |
| unemployment rate (%) | 68.49 | 72.41 | 51.61 | 65.41 |
| females, no lag | (79) | (53) | (44) | (176) |
| unemployment rate (%) | 78.48 | 66.04 | 61.36 | 70.45 |
| females, behind | (107) | (55) | (29) | (191) |
| unemployment rate (%) | 67.29 | 61.82 | 72.41 | 66.49 |

Source: Survey data.

Note: Numbers in round brackets show the sample size of each cell. no lag refers to respondents who were not behind the regular grade progression at the time of leaving the school, behind refers to respondents who were behind.

TABLE 5: Ratio of discouraged job seekers to unemployed among respondents

| age range | 20-25 | 26-30 | 31-35 | total |
|---|---|---|---|---|
| males, with matric (%) | 16.13 | 20.00 | 0.00 | 15.00 |
| LFJ | [40] | [7] | [8] | [55] |
| NLFJ | [9] | [3] | [9] | [21] |
| unemployed | 31 | 5 | 4 | 40 |
| males, no matric (%) | 8.70 | 11.90 | 19.23 | 11.68 |
| LFJ | [80] | [53] | [27] | [160] |
| NLFJ | [27] | [15] | [16] | [58] |
| unemployed | 69 | 42 | 26 | 137 |
| females, with matric (%) | 19.44 | 11.11 | 15.79 | 16.44 |
| LFJ | [40] | [25] | [23] | [88] |
| NLFJ | [20] | [7] | [6] | [33] |
| unemployed | 36 | 18 | 19 | 73 |
| females, no matric (%) | 24.49 | 25.49 | 3.45 | 21.35 |
| LFJ | [91] | [48] | [36] | [175] |
| NLFJ | [35] | [28] | [8] | [71] |
| unemployed | 98 | 51 | 29 | 178 |
| males, no lag (%) | 8.00 | 0.00 | 14.29 | 6.67 |
| LFJ | [65] | [42] | [18] | [125] |
| NLFJ | [18] | [7] | [11] | [36] |
| unemployed | 50 | 26 | 14 | 90 |
| males, behind (%) | 14.00 | 28.57 | 18.75 | 18.39 |
| LFJ | [55] | [18] | [17] | [90] |
| NLFJ | [18] | [11] | [14] | [43] |
| unemployed | 50 | 21 | 16 | 87 |
| females, no lag (%) | 24.19 | 14.29 | 0.00 | 16.13 |
| LFJ | [61] | [40] | [36] | [137] |
| NLFJ | [18] | [13] | [8] | [39] |
| unemployed | 62 | 35 | 27 | 124 |
| females, behind (%) | 22.22 | 29.41 | 19.05 | 23.62 |
| LFJ | [70] | [33] | [23] | [126] |
| NLFJ | [37] | [22] | [6] | [65] |
| unemployed | 72 | 34 | 21 | 127 |
| males (%) | 11.00 | 12.77 | 16.67 | 12.43 |
| LFJ | [120] | [60] | [35] | [215] |
| NLFJ | [36] | [18] | [25] | [79] |
| unemployed | 100 | 47 | 30 | 177 |
| females (%) | 23.13 | 21.74 | 8.33 | 19.92 |
| LFJ | [131] | [73] | [59] | [263] |
| NLFJ | [55] | [35] | [14] | [104] |
| unemployed | 134 | 69 | 48 | 251 |

Source: Survey data.

Note: Top row in each panel shows ratio of discouraged job seekers to the unemployed in percentage. Cell sample size equals to LFJ+NLFJ. LFJ = looking for a job, NLFJ = not looking for a job, both defined irrespective of employment status. Numbers in in the bottom row of each panel show the number of unemployed.

The labour market status by the age-gender group are shown in TABLE 2. Survey respondents are asked to give labour market status of each family members, including their readiness and willingness to work had a job was offfered.[*4] It shows large variations in unemployment rates between the age-

[*4] One may expect the information provided on the family members is less precise than the repondent's own status, however, this is how it is asked in the official South African statistics.

gender groups.[*5] First, there is a sequence of dips in the unemployment rates as we compare males of the minors relative to the youths, the youths relative to the adults. This follows a well known pattern found in nationally representative data. We find a similar sized dip among the females as we compare the youths relative to the adults, but no dip between the minors relative to the youths. Second, females have higher unemployment rates than males in prime age groups of youths and adults. This is also observed in the nationally representative data and is often argued as due to interruption of work by births, results of obtaining child support grants, higher incidence of cohabitation with parents who may support through unemployment than males, among others.

TABLE 3 shows the participation to labour force by educational qualification. Total group size is given in the parenthesis of the top row of each entry, unemployment rates in percentages in the second rows, and out of labour force in square brackets of third rows. We see that our sample consists of relatively many economically active individuals who are either working or looking for work among late 20's onwards, which may probably be due to the geographical proximity to employment opportunities.

TABLE 3 reveals several interesting facts behind the dips we observed in TABLE 2. For males, the first dip was driven by a large decrease among 20-25 for both the matriculated and the nonmatriculated which remain the same during 26-30, then decrease further by another large dip during 31-35 only among the matriculated. This reveals that there is a uniform reduction in unemployment rates up to 30 year olds, and a further large reduction is found only among the matriculated males aged 31-35. Looking at the females, the matriculated show a steady reduction up to 26-30 group, but the rate does not decrease further unlike the matriculated males. The nonmatriculated females have higher unemployment rates among 20-25, but the rate decreases steadily until ages 31-35. Given that the labour force participation rates are similar, this may reflect the differences in job arrival and acceotance rates between the groups. Another point we see is that the labour participation rates, defined by 1-(OLF)/(sample size), are lower among the nonmatriculated aged 16-19 for both gender. This is understandable that more younger individuals who have yet to finish matriculation, plausibly still in a school, are included in the nonmatriculated group.

## II.2 Information from respondent current status

TABLES 4 uses the current labour market status only of respondents.[*6] It summarises the labour market status by educational achievements and school progression at the time respondents left a school. Whether an individual is lagging from the regular grade progression is calculated by the age of leaving the school and the highest grades completed.[*7] Expectedly, we find a similar pattern of rate changes as this table uses a part of sample used in TABLE 3. While we see differences, there is no longer a large difference between rates in 31-35 among males of no lag and behind. This indicates that the ordely grade progression which can signal the quality of learning does not matter for employment as much as the matriculation. This is not the case for females. Females who are behind have lower rates untile 30 and a higher rate at 31-35.

TABLE 5 tabulates the discouraged job seekers and unemployed by school progression. Discour-

[*5] The older portion of minors, 18 and 19, are included in the definition of "youth" in official South African statistics. However, given the progression of school enrollment in recent years and low search efforts documented among relatively young individuals, it is questionable if we need to pay much attention to this age group because it is difficult to assess if they are seriously looking for a job to form a part of labour force. This is partly suggested from our sample in TABLE 3 where we see the majority of males and females without matriculation aged 16-19 are out of labour force.

[*6] While it is smaller in sample size than roster information, it has a richer set of information about school progression and job history. TABLE 4 gives the same summary statistics as in TABLE 3 that was based on the information of all family members. As we limit our sample to ages between 20 and 35, we have three age groups per gender.

[*7] It is possible that the age at entering the school may be diffferent from the regular school starting age. We have no information of it and assume that all respondents enter the school at the age of 6.

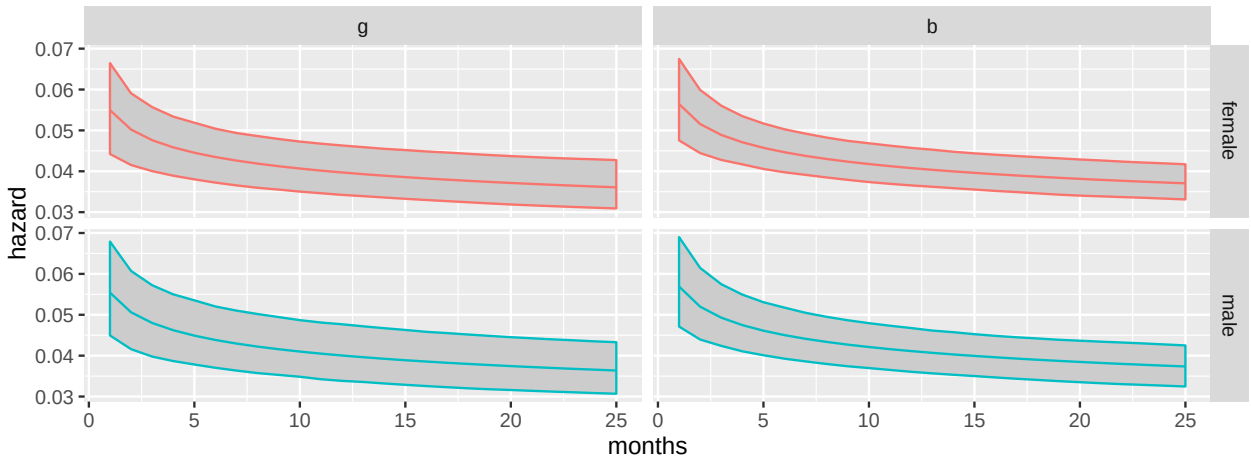


Figure 1 first unemployment hazard: weibull flexsurvreg

aged job seekers are non-searching unemployed. These individuals are without a job and are ready to work if a job is presented but do not actively search for it. They are formally (a part of labour force and is) classified as unemployed, although on the surface they look more like out of labour force. The first row shows the ratio of discouraged job seekers to the unemployed. This captures the proportion of "discouraged and not searching" individuals among the unemployed. Two rows in square brackets show the number of individuals among labour force ("looking for a job") and out of labour force ("not looking for a job") both irrespective of employment status. The sum of these two gives the total sample size of each category. The last row shows the number of unemployed.

We have a small number of discouraged job seekers than the nationally representative statistics may suggest. The reason behind it may be partly due the geographical proximity to employment opportunities, and also to the difference in the questions asked. In *Quarterly Labour Force Survey*, one is asked if one is willing to work when a job is offered. Our survey asks if the respondent is looking for a new job, be it actively or passively. While the former has the advantage of being widely used, asking the willingness to take a job without specifying the wage rate makes the interpretation difficult. The latter has the advantage of being simple and allowing a straightforward interpretation, but it has the disadvantage of not being widely used. As our survey does not aim to estimate the number of discouraged job seekers, we opted for the latter.

Table 5 shows the discouraged job seekers among the unemployed by matriculation status. It shows that discouraged job seekers are more often found among nonmatriculated females up to age 30. On the other hand, nonmatriculated males have higher discouraged job seekers relative to female counterparts in their 30's. This summary also shows relatively higher proportions of discouraged job seekers in the males and females of 26-30 and 31-35 who were behind in grade progression. The overall picture is that individuals with no matriculation or who lagged behind in grade progression get discouraged more often.

# III Labour cycles: Job history

## III.1 first unemployment spell

### III.1.1 Descriptive statistics at the start of spell

In the job history questionnaire, we asked the individuals to give all the regular jobs[*8] that he/she worked for after leaving the school. We have paid a particular attention to the first job to analyse the

[*8] Regular jobs are defined as term conrtacts or permanent contract jobs.

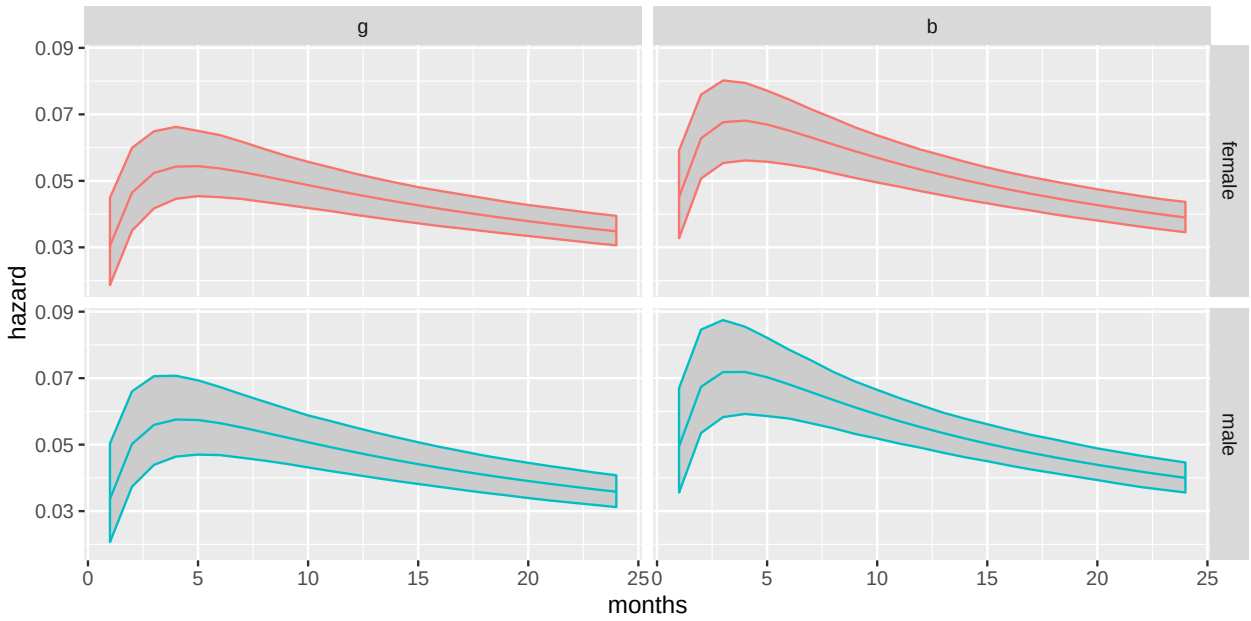


Figure 2 first unemployment hazard: generalized gamma flexsurvreg

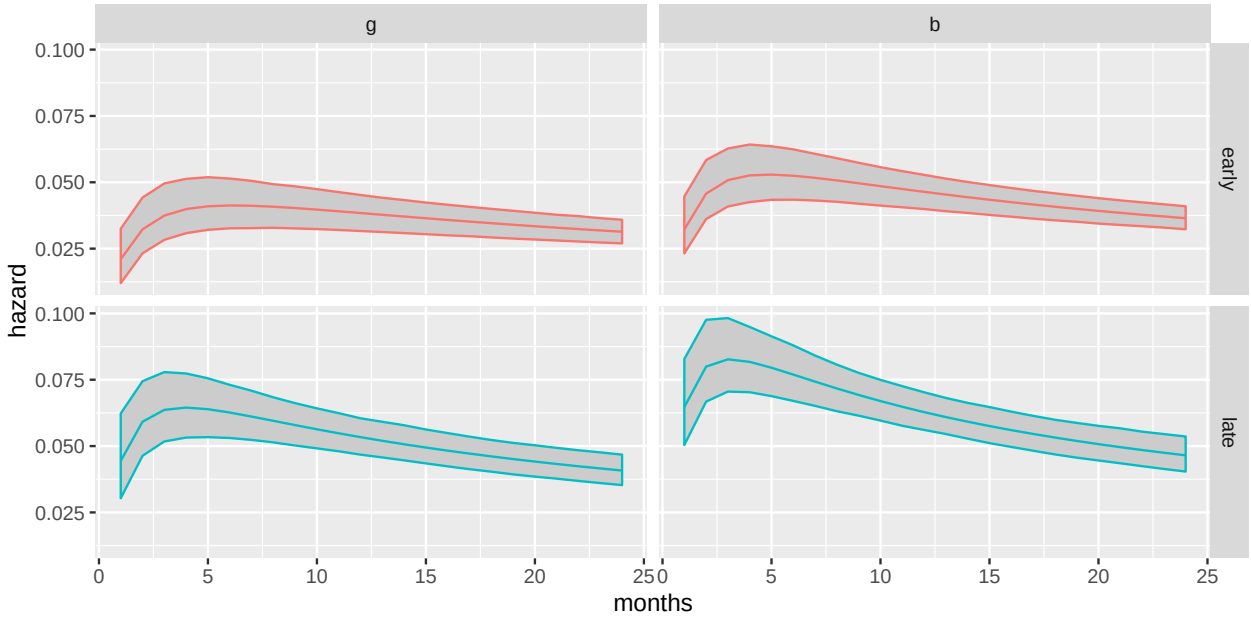


Figure 3 first unemployment hazard by cohort: generalized gamma flexsurvreg

school-to-work transition as precisely as possible. We supplemented the questionnaire with a special module on it.

TABLE 6 is a summary of duration among individuals classified into early (leaving the school before 2007) and late cohorts, males and females. The first row shows the proportion of matriculated individuals. We see that matriculation increased by 12.47% points among late cohorts. We also see the females have higher matriculation rates which may reflect that our female respondents are on average younger than the male respondents. The second row shows the duration of first unemployment spells in months. It is interesting to note that early cohorts faced slacker labour markets than the late cohorts and have spent more than double duration in unemployment. The third row shows the proportion of censored observation. Note late cohorts include 10.32% of right-censored individuals for their first unemployment duration. This is partly because they have just left the school as

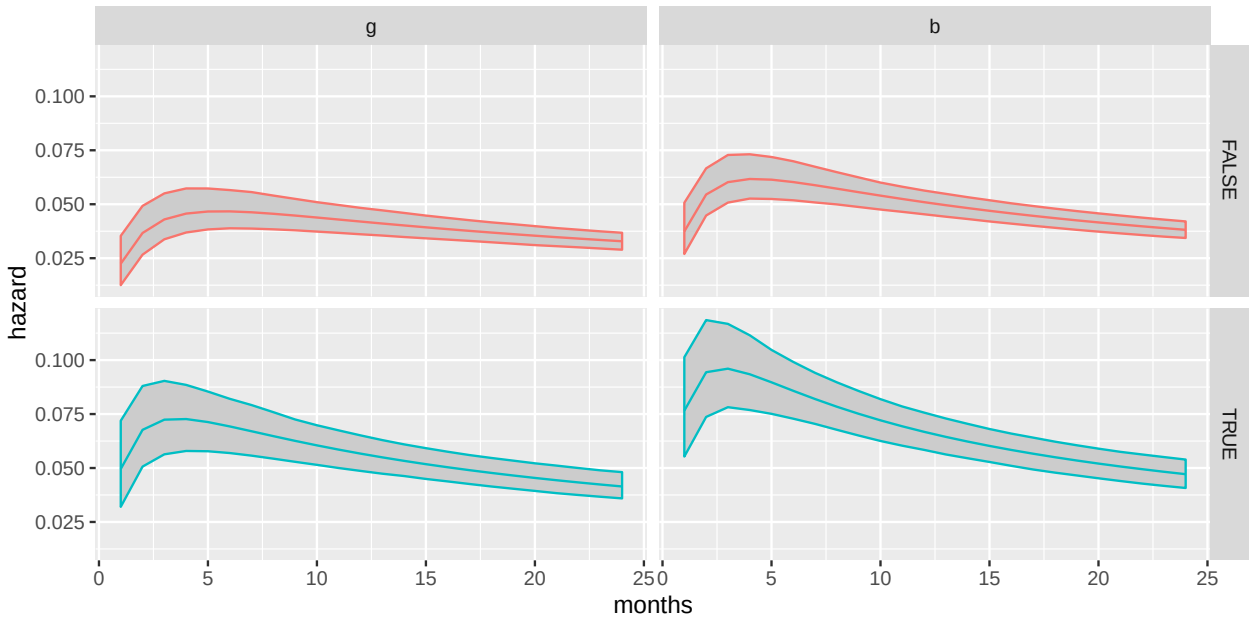


Figure 4 first unemployment hazard by education: generalized gamma flexsurvreg

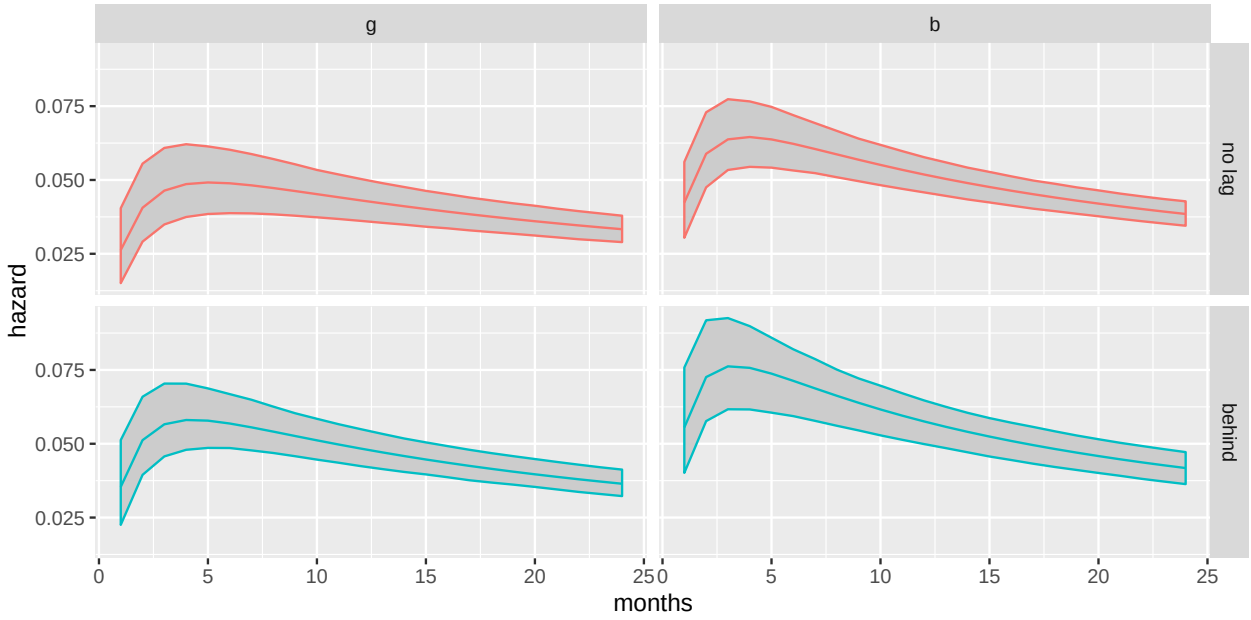


Figure 5 first unemployment hazard by progress: generalized gamma flexsurvreg

recently as a few months before the survey and still looking for the first job. The fourth row shows the first employment duration in months. It shows longer duration for males relative to females, and early relative to late cohorts. Ratios of corresponding censored observations are 16.90%, 12.78%, 8.97%, 19.48%, respectively. The proportion of censored observations are higher than unemployment spells, as they are of more recent spells. One notes that the male duration is longer than the females while the censoring is more frequent among the males. This indicates that, once landed on the first job, male employment is more secure and lasts longer than female employment. This reflects that matriculated males in the 30's have much lower unemployment rates than other groups.

TABLE 6: Duration and censoring

| | male | female | early | late |
|---|---|---|---|---|
| matriculated (%) | 26.9 | 33.6 | 23.9 | 36.4 |
| first unemployment (months) | 22.2 | 22.9 | 31.2 | 15.1 |
| unemployment censored (%) | 6.9 | 5.0 | 0.7 | 10.3 |
| first employment (months) | 27.0 | 22.9 | 33.8 | 16.0 |
| employment censored (%) | 16.9 | 12.8 | 9.0 | 19.5 |

Source: Survey data.

Note: early is cohorts who left school before 2007, late is cohorts who left school after 2007. Duration of first unemployment and first employment are expressed in months. unemployment censored and employment censored indicate fractions of right-censored observations.

We now estimate the parametric duration models. We use Weibull and generalised gamma as parametric hazard functions. Weibull hazard has an advantage of being simple but with a cost of being monotonic. The generalised gamma hazard is slower to converge, however, it has an advantage of allowing for nonmonotonic hazard against time and being more general that Weibull, gamma, and log normal are special cases of it[*9]. The generalised gamma hazard allows for richer duration dependence patterns.[*10]

In what follows, we estimate the hazard with the categorical variables and plot its fitted values and 95% confidence interval bands against time up to 25 months. All estimated standard errors are clustered at the community level. The panels indicated by "a" and "b" show communities a and b. We need to note that we cannot distinguish the true duration dependence from unobserved individual heterogeneity without a strong parametric assumption on the heterogeneity distribution. We need to keep in minds that, as our aim is to describe the patterns of spells across time, estimating the underlying duration dependence consistently is beyond the scope of this paper.

The Weibull hazard in FIGURE 1 shows a (monotonic, by its functional form nature) negative slope that is consistent with negative duration dependence. This implies that elapsed time of being unemployed will make the marginal chance of being employed smaller. This is consistent with an observation that the unemployed will tend to experience long spells. Negative duration dependence is not a surprising outcome for a process of positive selection. If the individuals with a good prospect are hired early, the remaining pool of students will be less employable and will face a lower chance of employment.

The patterns of generalized gamma hazard function in FIGURE 2 suggests that there is positive duration dependence in the early period of job search after leaving a school. Then dependence turns negative after about 4 months. The positive duration dependence in the earlier period implies that a group of students have a better chance of getting a job by waiting. The negative duration dependence in the later period implies that students who did not get employed earlier face an increasingly smaller chance of getting out of unemployment. This result also indicates that the negative duration dependence we inferred with Weibull hazard is strongly influenced by the latter part of the spell, and imposing monotonicity in hazard slope hides the initial positive dependency.

The gamma hazard by cohort of FIGURE 3 shows that early cohorts have a smaller transition probability than the later cohorts. This result is consistent with the previous table that early cohorts have longer unemployment spells. Negative duration dependence is stronger among the late cohorts, so waiting longer reduces the chance more rapidly than the early cohorts.

The gamma hazard by school grade progression of FIGURE 5 shows that being behind had a higher chance of moving out of initial unemployment spells. This is a surprising result. However, such an advantage quickly fades and the hazard at 15th month shows virtually no difference between the two

[*9] See Jackson (2016) which uses Prentice (1974) parametrisation.

[*10] When there is a negative duration dependence in unemployment spells, the hazard rate of leaving unemployed state decreases as duration increases. This results in near permanent unemployment among some individuals who had experienced the longer unemployment spells than others for some reasons.

TABLE 7: Duration of first unemployment, generalised gamma

| covariates | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| sex (female = 1) | 0.056 | 0.067 | 0.098 | 0.081 | 0.113 | 0.117 | 0.117 |
| | (0.100) | (0.103) | (0.102) | (0.102) | (0.104) | (0.105) | (0.105) |
| community B | −0.225** | −0.222** | −0.275*** | −0.325*** | −0.398*** | −0.394*** | −0.389*** |
| | (0.105) | (0.105) | (0.105) | (0.110) | (0.114) | (0.113) | (0.113) |
| late cohort | | −0.283*** | −0.248*** | −0.241** | −0.271*** | −0.491** | −0.491** |
| | | (0.107) | (0.105) | (0.105) | (0.106) | (0.275) | (0.275) |
| leaving year unemployment/population | | −3.875 | −1.550 | −1.446 | −1.225 | −1.399 | −1.252 |
| | | (4.044) | (4.049) | (4.037) | (4.064) | (4.082) | (4.089) |
| matriculated | | | −0.402*** | −0.440*** | −0.415*** | −0.711*** | −0.708*** |
| | | | (0.111) | (0.114) | (0.120) | (0.196) | (0.196) |
| no lag in progression | | | | 0.159* | 0.153* | 0.063 | 0.069 |
| | | | | (0.109) | (0.108) | (0.172) | (0.172) |
| number of adults | | | | | 0.083*** | 0.099** | 0.094* |
| | | | | | (0.035) | (0.058) | (0.059) |
| number of matriculated adults | | | | | −0.059 | −0.126 | −0.128 |
| | | | | | (0.065) | (0.109) | (0.109) |
| number of children | | | | | −0.004 | −0.004 | −0.002 |
| | | | | | (0.042) | (0.043) | (0.043) |
| number of elderly | | | | | 0.035 | 0.049 | 0.079 |
| | | | | | (0.082) | (0.081) | (0.100) |
| father employed | | | | | 0.283** | 0.151 | 0.136 |
| | | | | | (0.148) | (0.254) | (0.255) |
| mother employed | | | | | 0.039 | −0.039 | −0.040 |
| | | | | | (0.114) | (0.191) | (0.191) |
| matriculated * late cohort | | | | | | 0.445** | 0.435** |
| | | | | | | (0.242) | (0.242) |
| no lag in progression * late cohort | | | | | | 0.101 | 0.101 |
| | | | | | | (0.215) | (0.215) |
| number of adults * late cohort | | | | | | −0.021 | −0.021 |
| | | | | | | (0.072) | (0.072) |
| number of matriculated adults * late cohort | | | | | | 0.098 | 0.101 |
| | | | | | | (0.134) | (0.134) |
| father employed * late cohort | | | | | | 0.204 | 0.215 |
| | | | | | | (0.305) | (0.306) |
| mother employed * late cohort | | | | | | 0.130 | 0.124 |
| | | | | | | (0.235) | (0.235) |
| per member grant (R1000) | | | | | | | −0.179 |
| | | | | | | | (0.348) |
| logL | −2542 | −2080 | −2073 | −2072 | −2066 | −2063 | −2062 |
| AIC | 5094 | 4173 | 4162 | 4162 | 4162 | 4167 | 4169 |
| events | 612 | 519 | 519 | 519 | 519 | 519 | 519 |
| n | 650 | 556 | 556 | 556 | 556 | 556 | 556 |
| (a) matric + matric*late = 0 | | | | | | 0.040 | 0.037 |
| (b) no lag + no lag*late = 0 | | | | | | 0.228 | 0.213 |
| (c) (a) and (b) combined | | | | | | 0.096 | 0.088 |

Note: Combined hypothesis tests results show respective $p$ values of Wald tests. Parameters of generalised gamma distribution are omitted. See also the footnotes in TABLE 14.

groups. FIGURE 4 shows the highest level of hazard among FIGURE 2-5. This shows that matriculation still increases a chance of employment.

## III.2 Parametric hazard estimation

We summarise the estimated results of foregoing figures more systematically in TABLE 7. We will use only the generalised gamma for estimating duratiom models in this section due to its flexibility.[*11] In the column (1) of TABLES 7, we regressed the first unemployment duration on gender and

[*11] Majority of estimates are similar to Weibull estimates in TABLE 14. We see the differences in matriculated and cluster which may be due to generalised gamma regressions do not use intercept terms. Other differences are seen in positive statistically significant estimates on number of adults.

community dummies. Gender dummy turned out to be statistically not significant, and it is a general pattern in all the estimation specifications. Community dummy remains statistically significant in all specifications. In the column (2), we have large negative estimates on late cohort. This remains statistically significant in the all other specifications and we can conclude that the late cohorts have shorter unemployment spells than the early cohorts. This is rather surprising as the previous literature informs us that the youth unemployment rate has been steadily increasing since the late 1990's which corresponds to the first half of early cohorts through the late cohort. In (2), we also add leaving year unemployment/population among adults aged 18-64 in the Western Cape Province which captures the aggregate labour market tightness at school leaving years. This is motivated by the scarring effect literature which shows long lasting negative impacts of entering the labour market in a recessionary period (Heckman and Borjas, 1980; Ruhm, 1991; Arulampalam et al., 2000; Gregg, 2001; Burgess et al., 2003; D'Addio and Rosholm, 2005; Oreopoulos et al., 2012; Hershbein, 2012). Estimates show that the signs are opposite from theoretical predictions and are statistically not significant in all specificaions. We thus fail to find contemporaneous effects of aggregate labour market tightness on the initial employment.

We sequentially add matriculated in (3) and no lag in progression in (4). matriculated are all negative and statistically significant in all specifications. This is expected on the assumption that having matriculated provides a signal for unobservable productivity. Positive estimates on no lag in progression are also not surprising as the speed of grade progression is expected to be positively correlated with the rates of human capital accumulation. The estimates become not statistically significant as we add more covariates.

In (5), we added household structure variables. We have positive and statistically significant estmates on number of adults. As larger families with more adults tend to have more unemployed and be poorer in terms of per member income, this may capture the association of not connected to the job related network. father employed and mother employed have positive point estimates, which are at odds with an expectation that parents with jobs may give connections with future jobs. However, estimates become statistically not significant once we add other covariates. Estimates on number of elderly and per member grant (R1000) show that the chance of receiving grants is not associated with longer unemployment duration.

In (6), we added interaction terms of late cohort to see if the level effect estimates vary by timing of leaving the school. This is motivated by the discussion that the recent diplomas have a higher noise-to-signal ratio because grade progression had become more lenient towards academic underachievers. Results show that matriculated * late cohort estimates are all positive and statistically significant. This may reflect that the signaling benefits of matriculation are reduced for the late cohorts, or the late cohort matriculated are better financially placed to have a longer search period. If the late cohorts are better financially placed, we would expect them to be cohabitating with less adults or less matriculated adults relative to early cohorts. To examine the latter possibility, in (6), we included the interactions of matriculated adults * late and adult * late along with number of adult members and number of adult magtriculated members. Neither is found to be statistically significant nor in the expected sign. In the row (a), we tested for joint significance of matriculation and matriculation of late cohorts, and the null of no joint significance is rejected. Interactions no lag in progression * late cohort do not give statistically significant estimates.

# IV First unemployment and subsequent employment intensity

In this section, we consider the employment in the first years after leaving the school. If there is a scarring effect of initial unemployment duration, a shorter first unemployment spell is correlated with longer or more frequent employment in the later years. This is *lagged duration dependence* as defined in Heckman and Borjas (1980).

TABLE 8: First employment duration up to 5 years

| covariates | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| (female = 1) | −0.166** | −0.141* | −0.131 | −0.112 | −0.116 | −0.084 |
| | (0.096) | (0.106) | (0.109) | (0.119) | (0.109) | (0.120) |
| unemployment duration (months) | −0.021*** | −0.023*** | −0.027*** | −0.028*** | −0.027*** | −0.027*** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| community B | 0.252*** | 0.313*** | 0.318*** | 0.375*** | 0.283*** | 0.336*** |
| | (0.097) | (0.108) | (0.111) | (0.128) | (0.114) | (0.127) |
| matriculated | | | 0.264** | 0.311** | 0.184* | 0.233* |
| | | | (0.122) | (0.138) | (0.131) | (0.143) |
| late cohort | | | −0.029 | −0.060 | −0.028 | −0.076 |
| | | | (0.140) | (0.158) | (0.143) | (0.165) |
| no lag in progression | | | 0.119 | 0.131 | 0.144 | 0.153 |
| | | | (0.115) | (0.125) | (0.116) | (0.128) |
| leading average U/population | | | −7.072 | −7.446 | −5.788 | −6.316 |
| | | | (9.166) | (10.078) | (9.208) | (10.281) |
| number of adults | | | | | −0.025 | −0.043 |
| | | | | | (0.039) | (0.042) |
| number of matriculated adults | | | | | 0.119* | 0.158** |
| | | | | | (0.076) | (0.081) |
| number of elderly | | | | | 0.050 | 0.042 |
| | | | | | (0.087) | (0.095) |
| n | 290 | 290 | 215 | 215 | 215 | 215 |
| events | 276 | 276 | 205 | 205 | 205 | 205 |
| AIC | 1970 | 1965 | 1521 | 1522 | 1523 | 1523 |
| logL | −980 | −976 | −751 | −751 | −750 | −749 |
| distribution | W | gΓ | W | gΓ | W | gΓ |

Note: *, **, *** show statistical significance at 10, 5, 1%, respectively. Clustered standard errors are shown in parenthesis. Events are counts of end of spells. *n* is sample size. W stands for Weibull, gΓ for generalised gamma distributions. Duration is estimated in accelerated failure time (AFT) representation.

TABLE 9: First employment duration up to 2 years

| covariates | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| (female = 1) | −0.197*** | −0.169** | −0.173** | −0.184** | −0.157** | −0.179** |
| | (0.081) | (0.091) | (0.087) | (0.096) | (0.088) | (0.096) |
| unemployment duration (months) | −0.021*** | −0.026*** | −0.030*** | −0.036*** | −0.029*** | −0.036*** |
| | (0.001) | (0.002) | (0.001) | (0.003) | (0.001) | (0.006) |
| community B | 0.015 | −0.015 | 0.117* | 0.079 | 0.065 | 0.001 |
| | (0.085) | (0.094) | (0.091) | (0.101) | (0.095) | (0.109) |
| matriculated | | | 0.193** | 0.242** | 0.155* | 0.193** |
| | | | (0.099) | (0.109) | (0.101) | (0.112) |
| late cohort | | | −0.039 | −0.093 | −0.033 | −0.091 |
| | | | (0.087) | (0.097) | (0.088) | (0.129) |
| no lag in progression | | | 0.126* | 0.112 | 0.133* | 0.115 |
| | | | (0.095) | (0.103) | (0.095) | (0.106) |
| leading average U/population | | | −0.575 | −1.800 | −1.127 | −3.641 |
| | | | (4.212) | (4.619) | (4.249) | (10.966) |
| number of adults | | | | | −0.041* | −0.096** |
| | | | | | (0.029) | (0.052) |
| number of matriculated adults | | | | | 0.092** | 0.145** |
| | | | | | (0.053) | (0.065) |
| number of elderly | | | | | −0.046 | −0.095 |
| | | | | | (0.067) | (0.084) |
| n | 495 | 495 | 402 | 402 | 402 | 402 |
| events | 423 | 423 | 336 | 336 | 336 | 336 |
| AIC | 2573 | 2557 | 2064 | 2055 | 2066 | 2050 |
| logL | −1282 | −1272 | −1023 | −1017 | −1021 | −1012 |
| distribution | W | gΓ | W | gΓ | W | gΓ |

Note: *, **, *** show statistical significance at 10, 5, 1%, respectively. Clustered standard errors are shown in parenthesis. Events are counts of end of spells. *n* is sample size. W stands for Weibull, gΓ for generalised gamma distributions. Duration is estimated in accelerated failure time (AFT) representation.

We first consider the employment duration in the first 5 years after leaving school. In TABLE 8, we estimated the first employment duration in a window up to 5 years after leaving school on lagged unemployment duration and other covariates. We have dropped apparent errors in wage

reports whose average wage exceeds R400 per day which reduces our sample from 296 to 290. The sample size is 290 among which the comlete spell was observed for 276, or 95%. The estimates on lagged unemployment duration are negative across the specifications. The point estimates are stable and corresponds to a 1 month increase in lagged unemployment duration predicts 0.59 day (or $(1 - e^{-.02}) * 100 = (1 - 0.98) * 100\%$) decrease in employment duration. Although stable and statistically significant, the magnitude of relationship is small and even a 4 year unemployement will decrease the employment spell by less than 1 month. To check against a shorter window period whose effect is expected to be less stable yet with a larger sample size, we have estimated the same model for a 2 year window period with larger sample size of 1 in Table 9. Again, we have dropped wage anomalies that reduced the sample size from 511 to 495. A complete spell is observed in 423, or 85% of cases. Again, we see that lagged unemployment duration is related to employment duration by the proportion of about 2%. This suggests that the magnitude of covariation with the previous unemployment duration is small when we restrict our attention to the first employment spell out of school.

Given that duration $r$ of initial unemployment spell has a direct one-to-one relationship with the remaining duration $t - r$ in a fixed time interval $t$ that we observe, we will consider employment intensity during $m$ years after the end of inital unemployment spells:

$$e_{r,r+m} = \frac{\text{sum of employment duration between } r \text{ and } r+m}{m}.$$

Although $e_{r,r+m}$ have not used in the previous literature, it is a measure of employment duration that is normalised by the length of interval that we observe. This normalisation was introduced because we have a significant portion of young individuals in our sample with censored second spells who may have not finished.

We use a fractional logit model to examine how employment intensity changes with initial unemployment duration. Table 10 uses $e_{r,r+m}$ as a regressand. The estimates on duration of unemployment are all statistically not significant, implyng there is no strong indication of scarring effects. A positive association with matriculated and negative associations with late cohort and no lag in progression are found, with the latter two covariates become statistically not significant after 5 years. These estimates can extend the interpretation that better educational qualification is associated with not just shorter initial unemployment spells but also with more stable subsequent jobs. The lack of significance after 5 years for late cohort hints that employment status may become stable after 5 years irrespective of cohorts. This indicates that the late cohorts are characterised with shorter initial unemploymentn but with less frequent employment opportunities after a respondent had landed on the first job.

Another notable finding is that number of matriculated adults are positive and become statistically significant after 3 years. This suggests the long-term benefits in finding jobs by having better qualified adults in the same household, due probably to better home teaching and/or better job network.

In Table 11, we estimated the relationship between initial unemployment duration and subsequent wage level. To assess associations, we have taken a weighted average of wage rates per day of all subsequent jobs up to $m$ years. Weights are employment duration. None of the estimates on duration of unemployment is statistically significant. Only female has the robust negative point estimates with statistical significance. matriculated, late cohort, leading average U/population have some estimates that are statistically significant and have consistent signs across specifications.

TABLE 10: Employment intensity up to 5 years after first employment began

| | After 2 years | | | After 3 years | | | After 4 years | | | After 5 years | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| covariates | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| (Intercept) | 0.671*** (0.000) | 2.932*** (0.589) | 2.621*** (0.997) | 0.344*** (0.014) | 1.344** (0.644) | 1.118 (1.116) | 0.135*** (0.010) | −0.386 (1.739) | −0.691 (2.342) | −0.075* (0.057) | 0.728 (2.075) | 0.443 (2.920) |
| unemployment duration (months) | 0.097 (0.976) | −0.829 (0.665) | −0.881** (0.396) | 0.051 (0.874) | −0.808 (0.788) | −0.808* (0.502) | 0.141 (1.049) | −0.549 (1.283) | −0.529 (1.095) | 0.505 (1.067) | 0.345 (1.413) | 0.322 (1.157) |
| unemployment duration (months)2 | −0.207 (0.516) | 0.486*** (0.106) | 0.517*** (0.059) | −0.286 (0.443) | 0.359 (0.304) | 0.342*** (0.142) | −0.407 (0.543) | −0.007 (0.722) | −0.031 (0.665) | −0.658 (0.549) | −0.744 (0.950) | −0.669 (0.748) |
| (female = 1) | −0.292 (0.265) | −0.221 (0.198) | −0.179 (0.234) | −0.294 (0.277) | −0.177 (0.232) | −0.150 (0.252) | −0.326 (0.293) | −0.193 (0.264) | −0.151 (0.251) | −0.291* (0.215) | −0.181 (0.150) | −0.155 (0.143) |
| community B | 0.340*** (0.004) | 0.376*** (0.045) | 0.330*** (0.121) | 0.239*** (0.003) | 0.230*** (0.069) | 0.180* (0.122) | 0.159*** (0.002) | 0.178*** (0.067) | 0.129 (0.106) | 0.055*** (0.002) | 0.051 (0.108) | 0.021 (0.157) |
| matriculated | | 0.581*** (0.159) | 0.464*** (0.113) | | 0.511*** (0.072) | 0.408*** (0.073) | | 0.402*** (0.025) | 0.291*** (0.027) | | 0.485*** (0.074) | 0.413*** (0.104) |
| late cohort | | −0.845*** (0.217) | −0.888*** (0.222) | | −0.652*** (0.233) | −0.685*** (0.260) | | −0.594* (0.439) | −0.644* (0.480) | | −0.336 (0.474) | −0.388 (0.587) |
| no lag in progression | | −0.182*** (0.014) | −0.194*** (0.056) | | −0.176** (0.105) | −0.161*** (0.052) | | −0.121** (0.065) | −0.121*** (0.025) | | 0.046 (0.108) | 0.050 (0.073) |
| leading average U/population | | −14.249*** (5.458) | −12.784** (6.542) | | −5.700 (5.384) | −4.920 (6.905) | | 5.234 (13.823) | 6.581 (16.332) | | −6.717 (15.737) | −5.357 (19.937) |
| number of adults | | | 0.012 (0.094) | | | 0.020 (0.096) | | | 0.010 (0.079) | | | 0.011 (0.090) |
| number of matriculated adults | | | 0.190 (0.195) | | | 0.192** (0.105) | | | 0.207*** (0.026) | | | 0.161*** (0.019) |
| number of elderly | | | 0.044 (0.208) | | | −0.064 (0.117) | | | 0.016 (0.136) | | | −0.008 (0.096) |
| n | 498 | 405 | 405 | 465 | 372 | 372 | 409 | 315 | 315 | 367 | 274 | 274 |
| AIC | 678 | 540 | 542 | 648 | 508 | 512 | 569 | 446 | 446 | 501 | 385 | 390 |
| deviance [-2*loglik] | 352 | 270 | 268 | 315 | 241 | 238 | 257 | 193 | 190 | 214 | 154 | 153 |

Note: Fractional logit is estimated for employment intensity in $m$ year window after the end of first unemployment spell. Employment intensity is defined as $e_{r,r+m} = \frac{\text{sum of employment duration between } r \text{ and } r+m}{m}$ with $m = 2, 3, 4, 5$, where $r$ is the year of first employment. unemployment duration is first unemployment duration measured in months. leading average U/population are in fractions. See footnotes of TABLE 19

TABLE 11: Mean wage up to 5 years after first employment began

| | After 2 years | | | After 3 years | | | After 4 years | | | After 5 years | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| covariates | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| (Intercept) | 137.160*** | 86.847*** | 79.487** | 139.456*** | 86.869*** | 80.194** | 142.093*** | 96.872** | 97.757** | 144.040*** | 92.536* | 96.130* |
| | (4.745) | (30.446) | (31.712) | (4.732) | (33.426) | (34.517) | (4.699) | (40.302) | (41.273) | (4.702) | (55.778) | (56.402) |
| unemployment duration (months) | 0.028 | 0.114 | 0.098 | −0.003 | 0.067 | 0.048 | −0.016 | 0.043 | 0.032 | −0.026 | 0.004 | −0.018 |
| | (0.193) | (0.267) | (0.269) | (0.192) | (0.265) | (0.267) | (0.191) | (0.260) | (0.261) | (0.190) | (0.266) | (0.267) |
| unemployment duration (months)2 | − 0.000 | −0.001 | −0.001 | − 0.000 | −0.001 | −0.001 | − 0.000 | −0.001 | −0.001 | − 0.000 | −0.001 | −0.001 |
| | (0.001) | (0.003) | (0.003) | (0.001) | (0.003) | (0.003) | (0.001) | (0.003) | (0.003) | (0.001) | (0.003) | (0.003) |
| (female = 1) | −20.402*** | −21.404*** | −20.967*** | −20.578*** | −20.002*** | −19.603*** | −21.722*** | −21.959*** | −21.687*** | −21.570*** | −19.028*** | −18.785*** |
| | (4.848) | (5.044) | (5.089) | (4.834) | (5.013) | (5.053) | (4.804) | (5.054) | (5.083) | (4.796) | (5.248) | (5.267) |
| community B | −9.109* | −9.785* | −9.722* | −10.154** | −9.698* | −9.701* | −11.114** | −10.329* | −11.376** | −12.321** | −9.344 | −10.245* |
| | (5.119) | (5.521) | (5.639) | (5.105) | (5.488) | (5.612) | (5.072) | (5.526) | (5.651) | (5.060) | (5.776) | (5.902) |
| matriculated | | 13.288** | 12.898** | | 14.380** | 14.050** | | 11.568* | 11.057* | | 10.306* | 9.871 |
| | | (5.835) | (6.115) | | (5.820) | (6.065) | | (5.915) | (6.157) | | (6.151) | (6.380) |
| late cohort | | 7.652 | 7.225 | | 5.161 | 4.707 | | 3.297 | 3.352 | | 1.295 | 1.501 |
| | | (5.388) | (5.429) | | (5.716) | (5.763) | | (6.438) | (6.492) | | (7.996) | (8.036) |
| no lag in progression | | −1.275 | −1.304 | | −0.573 | −0.654 | | 0.746 | 0.977 | | 2.416 | 2.794 |
| | | (5.506) | (5.527) | | (5.477) | (5.496) | | (5.483) | (5.486) | | (5.707) | (5.703) |
| leading average U/population | | 3.315 | 3.532 | | 3.427 | 3.608 | | 2.887 | 2.786 | | 3.265 | 2.760 |
| | | (2.254) | (2.282) | | (2.526) | (2.548) | | (3.118) | (3.135) | | (4.361) | (4.372) |
| number of adults | | | 1.249 | | | 1.214 | | | 0.415 | | | 1.163 |
| | | | (1.648) | | | (1.633) | | | (1.616) | | | (1.645) |
| number of matriculated adults | | | 0.522 | | | 0.617 | | | 2.460 | | | 2.463 |
| | | | (3.187) | | | (3.186) | | | (3.135) | | | (3.178) |
| number of elderly | | | −0.536 | | | −0.578 | | | −5.601 | | | −6.477 |
| | | | (4.032) | | | (4.004) | | | (4.069) | | | (4.228) |
| n | 566 | 477 | 477 | 566 | 474 | 474 | 565 | 438 | 438 | 564 | 409 | 409 |
| R2 | 0.0289 | 0.0538 | 0.0496 | 0.0310 | 0.0501 | 0.0458 | 0.0363 | 0.0496 | 0.0494 | 0.0380 | 0.0355 | 0.0383 |
| F | 0.0004 | 0.0000 | 0.0003 | 0.0002 | 0.0001 | 0.0006 | 0.0001 | 0.0002 | 0.0006 | 0.0000 | 0.0040 | 0.0052 |

Note: leading average U/population are in percentages. See footnotes of TABLE 19

TABLE 12: Income earned up to 5 years after first employment began

| | After 2 years | | | After 3 years | | | After 4 years | | | After 5 years | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| covariates | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| (Intercept) | 128.335*** | 268.234*** | 256.338*** | 149.640*** | 298.878*** | 286.199*** | 164.196*** | 334.469*** | 337.800*** | 171.702*** | 360.273*** | 380.291*** |
| | (12.956) | (61.797) | (64.310) | (13.707) | (69.601) | (71.707) | (13.973) | (91.259) | (93.434) | (14.178) | (129.692) | (131.228) |
| unemployment duration (months) | 0.098 | −1.003* | −1.014* | −0.013 | −1.086** | −1.122** | −0.050 | −1.710*** | −1.739*** | −0.069 | −2.072*** | −2.092*** |
| | (0.526) | (0.543) | (0.546) | (0.556) | (0.552) | (0.555) | (0.567) | (0.590) | (0.592) | (0.574) | (0.618) | (0.620) |
| unemployment duration (months)2 | −0.002 | 0.002 | 0.002 | −0.002 | 0.002 | 0.003 | −0.002 | 0.007 | 0.007 | −0.002 | 0.008 | 0.009 |
| | (0.004) | (0.005) | (0.005) | (0.004) | (0.006) | (0.006) | (0.004) | (0.006) | (0.006) | (0.004) | (0.006) | (0.006) |
| (female = 1) | −34.731*** | −25.534** | −24.203** | −46.562*** | −33.009*** | −31.503*** | −49.479*** | −35.736*** | −35.267*** | −48.679*** | −31.543** | −31.472** |
| | (13.236) | (10.237) | (10.321) | (14.002) | (10.439) | (10.497) | (14.283) | (11.445) | (11.506) | (14.462) | (12.203) | (12.255) |
| community B | −20.922 | −6.131 | −7.763 | −23.078 | −5.270 | −7.290 | −29.223* | −14.127 | −16.310 | −29.419* | −18.072 | −20.732 |
| | (13.977) | (11.207) | (11.436) | (14.787) | (11.427) | (11.660) | (15.080) | (12.513) | (12.793) | (15.258) | (13.431) | (13.732) |
| matriculated | | 15.029 | 12.378 | | 18.485 | 16.041 | | 27.704** | 27.123* | | 29.542** | 29.099* |
| | | (11.844) | (12.401) | | (12.118) | (12.599) | | (13.395) | (13.938) | | (14.303) | (14.844) |
| late cohort | | −72.792*** | −73.591*** | | −83.588*** | −84.578*** | | −78.791*** | −78.444*** | | −82.895*** | −81.313*** |
| | | (10.936) | (11.009) | | (11.901) | (11.973) | | (14.579) | (14.696) | | (18.592) | (18.698) |
| no lag in progression | | 5.517 | 5.969 | | 1.015 | 1.305 | | −3.474 | −2.930 | | −8.152 | −7.157 |
| | | (11.176) | (11.208) | | (11.405) | (11.418) | | (12.415) | (12.420) | | (13.269) | (13.269) |
| leading average U/population | | −8.127* | −7.539 | | −8.664 | −8.185 | | −9.635 | −9.963 | | −10.059 | −11.486 |
| | | (4.575) | (4.627) | | (5.259) | (5.293) | | (7.059) | (7.097) | | (10.141) | (10.172) |
| number of adults | | | 1.069 | | | 1.971 | | | 1.130 | | | 0.529 |
| | | | (3.342) | | | (3.392) | | | (3.658) | | | (3.827) |
| number of matriculated adults | | | 5.426 | | | 6.192 | | | 4.784 | | | 5.608 |
| | | | (6.463) | | | (6.619) | | | (7.096) | | | (7.395) |
| number of elderly | | | −5.512 | | | −8.214 | | | −13.846 | | | −16.812* |
| | | | (8.176) | | | (8.318) | | | (9.212) | | | (9.837) |
| n | 566 | 477 | 477 | 566 | 474 | 474 | 565 | 438 | 438 | 564 | 409 | 409 |
| R2 | 0.0104 | 0.1073 | 0.1048 | 0.0183 | 0.1428 | 0.1428 | 0.0226 | 0.1496 | 0.1499 | 0.0220 | 0.1674 | 0.1688 |
| F | 0.0425 | 0.0000 | 0.0000 | 0.0062 | 0.0000 | 0.0000 | 0.0021 | 0.0000 | 0.0000 | 0.0025 | 0.0000 | 0.0000 |

TABLE 13: Number of turnovers up to 5 years after first employment began

| | After 2 years | | | After 3 years | | | After 4 years | | | After 5 years | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Count model (truncated Poisson) | | | | | | | | | | | | |
| covariates | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| (Intercept) | −1.296*** | −2.273 | −2.602 | −0.639** | −1.895 | −2.089 | −0.451** | −3.215 | −3.375 | −0.404** | −0.996 | −1.527 |
| | (0.433) | (2.834) | (2.937) | (0.261) | (2.307) | (2.377) | (0.194) | (2.119) | (2.206) | (0.178) | (2.419) | (2.531) |
| unemployment duration (months) | −0.008 | −0.002 | −0.003 | −0.017* | −0.009 | −0.009 | −0.004 | −0.006 | −0.007 | −0.002 | −0.007 | −0.008 |
| | (0.010) | (0.012) | (0.012) | (0.010) | (0.011) | (0.011) | (0.004) | (0.007) | (0.008) | (0.003) | (0.007) | (0.007) |
| (female = 1) | 0.525 | 0.545 | 0.454 | 0.047 | 0.070 | 0.053 | 0.089 | −0.037 | −0.080 | 0.346* | 0.205 | 0.185 |
| | (0.487) | (0.501) | (0.515) | (0.317) | (0.342) | (0.349) | (0.235) | (0.257) | (0.260) | (0.205) | (0.222) | (0.225) |
| community B | −0.624 | −0.674 | −0.559 | −1.134 | −1.192 | −1.126 | −1.992*** | −2.038*** | −2.065*** | −1.831*** | −1.946*** | −1.961*** |
| | (1.032) | (1.048) | (1.066) | (0.723) | (0.744) | (0.752) | (0.712) | (0.727) | (0.734) | (0.505) | (0.521) | (0.529) |
| matriculated | | 0.064 | 0.511 | | 0.254 | 0.433 | | 0.192 | 0.286 | | 0.062 | 0.115 |
| | | (0.552) | (0.633) | | (0.407) | (0.452) | | (0.309) | (0.338) | | (0.285) | (0.308) |
| late cohort | | 0.091 | 0.165 | | 0.098 | 0.127 | | −0.278 | −0.330 | | −0.171 | −0.240 |
| | | (0.537) | (0.551) | | (0.442) | (0.458) | | (0.371) | (0.375) | | (0.366) | (0.375) |
| no lag in progression | | 0.102 | 0.065 | | 0.031 | 0.031 | | −0.117 | −0.136 | | −0.258 | −0.255 |
| | | (0.524) | (0.539) | | (0.372) | (0.374) | | (0.271) | (0.270) | | (0.227) | (0.227) |
| leading average U/population | | 0.061 | 0.075 | | 0.079 | 0.080 | | 0.233 | 0.246 | | 0.082 | 0.109 |
| | | (0.212) | (0.215) | | (0.180) | (0.181) | | (0.166) | (0.168) | | (0.191) | (0.195) |
| number of adults | | | 0.110 | | | 0.062 | | | 0.043 | | | 0.071 |
| | | | (0.151) | | | (0.120) | | | (0.097) | | | (0.078) |
| number of matriculated adults | | | −0.820 | | | −0.296 | | | −0.083 | | | −0.041 |
| | | | (0.547) | | | (0.283) | | | (0.192) | | | (0.159) |
| number of elderly | | | −0.178 | | | 0.008 | | | −0.225 | | | −0.081 |
| | | | (0.425) | | | (0.285) | | | (0.235) | | | (0.192) |
| Zero hurdle model (binomial) | | | | | | | | | | | | |
| (Intercept) | −0.761*** | −1.707 | −1.261 | −0.137 | 0.836 | 1.115 | 0.184 | 2.756* | 3.502** | 0.301* | 4.304* | 5.079** |
| | (0.186) | (1.434) | (1.494) | (0.162) | (1.385) | (1.441) | (0.159) | (1.673) | (1.740) | (0.158) | (2.286) | (2.342) |
| unemployment duration (months) | −0.009** | −0.012** | −0.012** | −0.002 | −0.011** | −0.011** | −0.004 | −0.016*** | −0.016*** | −0.005 | −0.020*** | −0.019*** |
| | (0.004) | (0.006) | (0.006) | (0.003) | (0.005) | (0.005) | (0.003) | (0.005) | (0.005) | (0.003) | (0.005) | (0.005) |
| (female = 1) | 0.014 | −0.295 | −0.319 | −0.211 | −0.464** | −0.475** | −0.090 | −0.197 | −0.223 | −0.068 | −0.046 | −0.069 |
| | (0.216) | (0.240) | (0.241) | (0.185) | (0.210) | (0.211) | (0.178) | (0.210) | (0.212) | (0.174) | (0.214) | (0.217) |
| community B | −1.701*** | −1.476*** | −1.460*** | −1.320*** | −1.241*** | −1.244*** | −1.188*** | −1.205*** | −1.257*** | −0.908*** | −0.895*** | −0.939*** |
| | (0.310) | (0.327) | (0.331) | (0.221) | (0.247) | (0.253) | (0.198) | (0.235) | (0.245) | (0.187) | (0.235) | (0.244) |
| matriculated | | −0.460 | −0.394 | | −0.706*** | −0.666** | | −0.400 | −0.356 | | −0.523** | −0.481* |
| | | (0.291) | (0.309) | | (0.258) | (0.269) | | (0.249) | (0.261) | | (0.251) | (0.261) |
| late cohort | | 0.163 | 0.192 | | −0.058 | −0.040 | | 0.188 | 0.250 | | 0.367 | 0.442 |
| | | (0.259) | (0.261) | | (0.239) | (0.241) | | (0.267) | (0.271) | | (0.327) | (0.331) |
| no lag in progression | | 0.639** | 0.646** | | 0.367 | 0.373* | | 0.276 | 0.288 | | 0.233 | 0.249 |
| | | (0.259) | (0.260) | | (0.227) | (0.227) | | (0.226) | (0.226) | | (0.232) | (0.232) |
| leading average U/population | | 0.065 | 0.048 | | −0.044 | −0.056 | | −0.173 | −0.203 | | −0.278 | −0.314* |
| | | (0.107) | (0.108) | | (0.106) | (0.107) | | (0.130) | (0.132) | | (0.179) | (0.181) |
| number of adults | | | −0.055 | | | −0.019 | | | −0.071 | | | −0.059 |
| | | | (0.081) | | | (0.069) | | | (0.070) | | | (0.069) |
| number of matriculated adults | | | −0.104 | | | −0.037 | | | 0.010 | | | 0.014 |
| | | | (0.170) | | | (0.139) | | | (0.135) | | | (0.132) |
| number of elderly | | | −0.005 | | | −0.138 | | | −0.285* | | | −0.305* |
| | | | (0.187) | | | (0.168) | | | (0.172) | | | (0.175) |
| n | 566 | 477 | 477 | 566 | 474 | 474 | 565 | 438 | 438 | 564 | 409 | 409 |
| logL | −322 | −274 | −272 | −438 | −364 | −363 | −515 | −396 | −394 | −562 | −410 | −407 |

Note: Regressand is the number of employment after the first job. A zero hurdle model is estimated. Count model refers to the estimates of count model likelihood component, Zero hurdle model refers to the estimates of zero hurdle likelihood component. leading average U/population are in percentages. See footnotes of TABLE 19

In TABLE 12, we further checked the correlations with subsequent labour incomes earned. Monthly incomes are computed by multiplying employment duration with daily wage rates*25 (days). The estimates on duration of unemployment are negative and become statistically significant after 4 years, which is not surprising as we use the total income rather than the average montly income. At after 5 years, point estimates in (11) and (12) indicate about a R2000 decrease for a month of initial unemployment spell, which translates to negligible magnitude of R33 per month in 5 years. As in the previous table, female have robustly negative estimates across specifications which are expected as they are paid lower wage rates while their unemployment rates are higher. late cohort is associated with lower labour incomes. Together with shorter initial unemployment spells, smaller employment intensity, and statistically zero wage changes among the late cohorts relative to the early cohorts, this indicates that the rates of labour market turnover might have become higher yet the employment spells had become sufficiently shorter and less frequent that result in smaller incomes.

In TABLE 13, we further checked the correlations with subsequent labour market turnovers. We use number of employment after the first job up to 5 years. We opt for a zero hurdle model as we have many zero turnovers and a simple Poisson regression will impose a strong restriction on estimation. We find majority of estimates on duration of unemployment in the zero hurdle component to be negative and statistically significant. This indicates that if an individual seaches longer, there will be fewer instances of zero job turnover. This implies that individuals with a shorter initial unemployment spell tends to enjoy more stable employment.

Overall, we find little indication that the initial unemployment duration is correlated with the subsequent employment spells. Regardless of the differences in search strategy that job searchers may employ, prospective employers do not take into considerations if an individual spent a short or long period to land on the first job. This may show that employers do not rely on the signals they obtain from the candidate's initial labour market transactions. The implications for the job searchers are that, first, one can ignore the reputation concerns when searching for the first job, and second, one will face with struggles in establishing signals of their productivity. This is in contrast with the previous literature that uses the data from developed economies.

# V Conclusion

We have used the sampled data from two urban townships in the Cape Town, South Africa. We have utilised the rich job history information collected and estimated the duration models for initial unemployment spells, and then estimated their relationship with subsequent employment.

While we observe a negative correlation between initial unemployment spells and matriculation and other school related variables, we do not find a dynamic relationship indicative of scarring effects. When we look at the employment duration in the 5 year window, there is no statistically significant relationship between the first unemployment spell and future employment. This implies that employers do not rely on the labour turnover signals they observe among the young job searchers, and job searchers should face some struggle in establishing their reputation. Another feature we find is that unemployment intensity tends to increase with the number of adults with matriculation in the household. This may be indicative of network effects in job stability. Together, we observe that South African labour markets are poorly equipped in sharing the information, and informal arrangements through kinship are used to fill the gap.

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# Appendix A First unemployment duration

## A.1 Parametric duration models

In Table 14 and Table 7, we see that longer unemployment duration is associated with being an early cohort, being at per with regular grade progression, and not having matriculation. All are stable across specifications and parametric assumptions. Given a great difficulty to land on a job for the early cohort, longer unemployment duraion results with earlier cohorts. Matriculation in later cohorts still seems to work as an endorser for a job applicant but only at a lesser degree.

## A.2 Cox proportional hazard with time-dependent covariates

We introduce additional covariates to duration models in Cox proportional hazard models. Cox proportinal hazard models have an advantage of being semiparametric and allowing for time-dependent covariates and coefficients.[*12] This section is added as a robustness check on fully parametric duration models.

Most of estimates on covariates in Table 15 are qualitatively similar to parametric duration mod-

[*12] One needs to choose the same parametrisation when comparing the results of Cox models and other parametric models, namely, proportional hazard representation. One also needs to note that Cox PH models have different sign conventions that the signs will be opposite of parametric duration models.

TABLE 14: Duration of first unemployment, Weibull

| covariates | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Intercept | 3.167*** | 4.046*** | 3.857*** | 3.831*** | 3.620*** | 3.774*** | 3.776*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| sex (female = 1) | 0.009 | 0.005 | 0.024 | 0.022 | 0.059 | 0.056 | 0.055 |
| | (0.097) | (0.528) | (0.526) | (0.518) | (0.543) | (0.560) | (0.560) |
| community B | −0.031 | −0.102 | −0.155 | −0.238** | −0.285*** | −0.286 | −0.284 |
| | (0.094) | (3.812) | (0.104) | (0.097) | (0.103) | (0.213) | (0.295) |
| late cohort | | −0.395*** | −0.331*** | −0.310*** | −0.345*** | −0.473*** | −0.476*** |
| | | (0.093) | (0.092) | (0.091) | (0.094) | (0.094) | (0.094) |
| leaving year unemployment/population | | −5.421*** | −3.313*** | −3.584*** | −3.377*** | −3.931*** | −3.811*** |
| | | (0.094) | (0.095) | (0.094) | (0.096) | (0.244) | (0.244) |
| matriculated | | | −0.383 | −0.438 | −0.454 | −0.742 | −0.736 |
| | | | (3.824) | (3.771) | (3.816) | (3.881) | (3.904) |
| no lag in progression | | | | 0.244** | 0.233** | 0.278 | 0.283 |
| | | | | (0.105) | (0.110) | (0.177) | (0.178) |
| number of adults | | | | | 0.049 | 0.054 | 0.050 |
| | | | | | (0.097) | (0.149) | (0.150) |
| number of matriculated adults | | | | | −0.047 | −0.095* | −0.095* |
| | | | | | (0.032) | (0.054) | (0.055) |
| number of children | | | | | −0.029 | −0.031 | −0.029 |
| | | | | | (0.059) | (0.095) | (0.095) |
| number of elderly | | | | | 0.045 | 0.047 | 0.061 |
| | | | | | (0.040) | (0.040) | (0.040) |
| father employed | | | | | 0.279*** | 0.151** | 0.143 |
| | | | | | (0.074) | (0.074) | (0.089) |
| mother employed | | | | | 0.137 | 0.104 | 0.104 |
| | | | | | (0.135) | (0.222) | (0.224) |
| matriculated * late cohort | | | | | | 0.445*** | 0.436** |
| | | | | | | (0.170) | (0.170) |
| no lag in progression * late cohort | | | | | | −0.132 | −0.136 |
| | | | | | | (0.215) | (0.218) |
| number of adults * late cohort | | | | | | −0.008 | −0.007 |
| | | | | | | (0.191) | (0.192) |
| number of matriculated adults * late cohort | | | | | | 0.093 | 0.094 |
| | | | | | | (0.066) | (0.066) |
| father employed * late cohort | | | | | | 0.210* | 0.218* |
| | | | | | | (0.121) | (0.122) |
| mother employed * late cohort | | | | | | 0.045 | 0.041 |
| | | | | | | (0.272) | (0.274) |
| per member grant (R1000) | | | | | | | −0.087 |
| | | | | | | | (0.214) |
| logL | −2572 | −2096 | −2090 | −2086 | −2080 | −2076 | −2076 |
| AIC | 5152 | 4204 | 4193 | 4189 | 4188 | 4193 | 4195 |
| events | 612 | 519 | 519 | 519 | 519 | 519 | 519 |
| n | 650 | 556 | 556 | 556 | 556 | 556 | 556 |
| (a) matric + matric*late = 0 | | | | | | 0.030 | 0.029 |
| (b) no lag + no lag*late = 0 | | | | | | 0.243 | 0.239 |
| (c) (a) and (b) combined | | | | | | 0.077 | 0.075 |

Note: *, **, *** show statistical significance at 10, 5, 1%, respectively. Clustered standard errors are shown in parenthesis. Estimates are shown in proporshonal hazard representation, positive estimates imply longer duration. Wald tests and score tests are run against the null of all covariates are zero. Events are counts of end of spells. *n* is sample size. Parameters of Weibull distribution are omitted.

els.*[13] Matriculation, late cohorts, lagging in progress are all associated with shorter unemployment spells. TABLE 16 introduces time-depedent covariates. Relative magnitude of interaction terms matriculated * late cohort is much larger than Weibull and generalised gamma duration models. The most notable difference from previous tables is that per member grant (R1000) is now statistically significant and large in size. This and its month interaction terms show an interesting pattern that per member grant (R1000) initially has a positive association in terminating unemployment, but such relationship fades as months pass. While most of time-dependent covariates have statistically

*[13] Except that the signs of estimates are reversed from the previous parametric estimates, for both time-dependent in TABLE 15 and time-varying coefficients in TABLE 16. These are due to sign convetions of Cox models.

TABLE 15: Hazard of first unemployment, Cox proportional hazard

| covariates | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| community B | −0.055*** | −0.106*** | −0.153*** | −0.230*** | −0.278*** | −0.278*** | −0.276*** |
| | (0.007) | (0.016) | (0.020) | (0.027) | (0.017) | (0.029) | (0.025) |
| female | −0.013 | −0.010 | −0.030 | −0.026 | −0.055 | −0.052 | −0.050 |
| | (0.024) | (0.069) | (0.068) | (0.073) | (0.043) | (0.057) | (0.060) |
| late | | 0.338*** | 0.288*** | 0.277*** | 0.309*** | 0.422* | 0.426* |
| | | (0.070) | (0.059) | (0.054) | (0.081) | (0.329) | (0.331) |
| leaving year unemployment/population | | 3.404 | 1.480 | 1.667 | 1.572 | 2.160 | 2.026 |
| | | (3.063) | (3.045) | (2.945) | (3.231) | (3.318) | (3.137) |
| matriculated | | | 0.353*** | 0.410*** | 0.420*** | 0.709*** | 0.704*** |
| | | | (0.031) | (0.043) | (0.083) | (0.224) | (0.212) |
| no lag in progression | | | | −0.229*** | −0.221*** | −0.279*** | −0.285*** |
| | | | | (0.016) | (0.006) | (0.048) | (0.041) |
| number of adults | | | | | −0.052* | −0.059 | −0.055 |
| | | | | | (0.036) | (0.094) | (0.097) |
| number of matriculated adults | | | | | 0.054 | 0.103 | 0.104 |
| | | | | | (0.069) | (0.153) | (0.151) |
| number of children | | | | | 0.020 | 0.023 | 0.022 |
| | | | | | (0.023) | (0.021) | (0.021) |
| number of elderly | | | | | −0.045*** | −0.047** | −0.062* |
| | | | | | (0.017) | (0.020) | (0.039) |
| father employed | | | | | −0.253*** | −0.121 | −0.112 |
| | | | | | (0.025) | (0.129) | (0.143) |
| mother employed | | | | | −0.134*** | −0.111** | −0.111** |
| | | | | | (0.045) | (0.063) | (0.065) |
| matriculated * late cohort | | | | | | −0.441*** | −0.432*** |
| | | | | | | (0.154) | (0.140) |
| no lag in progression * late cohort | | | | | | 0.146* | 0.151* |
| | | | | | | (0.113) | (0.105) |
| number of adults * late cohort | | | | | | 0.011 | 0.010 |
| | | | | | | (0.075) | (0.077) |
| number of matriculated adults | | | | | | −0.095 | −0.096 |
| | | | | | | (0.110) | (0.108) |
| father employed * late cohort | | | | | | −0.217** | −0.226** |
| | | | | | | (0.107) | (0.118) |
| mother employed * late cohort | | | | | | −0.033 | −0.029 |
| | | | | | | (0.130) | (0.135) |
| per member grant (R1000) | | | | | | | 0.096 |
| | | | | | | | (0.108) |
| logL | −3363 | −2766 | −2760 | −2757 | −2751 | −2748 | −2747 |
| Wald test | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Score test | 0.803 | 0.005 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| events | 612 | 519 | 519 | 519 | 519 | 519 | 519 |
| n | 650 | 556 | 556 | 556 | 556 | 556 | 556 |

Note: *, **, *** show statistical significance at 10, 5, 1%, respectively. Clustered standard errors are shown in parenthesis. Wald tests and score tests are run against the null of all covariates are zero. Events are counts of end of spells. *n* is sample size. Plots of Schoenfeld residuals (not shown) indicate baseline hazard is constant through time except for matric in some specifications. Results are available from authors upon request.

signidficant estimates, we note that matriculation * month * late cohort has positive values that matriculation is associated with less and less chance of continuing unemployment but only for late cohorts. This is a relection that early cohorts had longer unemployment spells.

TABLE 16: Hazard of first unemployment, Cox proportional hazard with time-varying coefficients

| covariates | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| community B | −0.170*** | −0.255*** | −0.291*** | −0.341*** | −0.450*** | −0.445*** |
| | (0.003) | (0.023) | (0.023) | (0.004) | (0.090) | (0.109) |
| female | −0.069 | −0.044 | −0.076** | −0.092* | −0.178*** | −0.193*** |
| | (0.080) | (0.035) | (0.039) | (0.058) | (0.026) | (0.041) |
| late | | 0.200*** | 0.161*** | 0.163*** | 0.221*** | 0.627*** |
| | | (0.052) | (0.051) | (0.033) | (0.061) | (0.246) |
| leaving year unemployment/population | | 9.324** | 8.026** | 6.329* | 7.922** | 7.485* |
| | | (4.067) | (3.795) | (4.299) | (3.581) | (4.807) |
| matriculated | | | 0.253*** | 0.280*** | 0.256*** | 0.612*** |
| | | | (0.029) | (0.022) | (0.015) | (0.032) |
| no lag in progression | | | | −0.036 | 0.032 | 0.150*** |
| | | | | (0.078) | (0.027) | (0.031) |
| number of adults | | | | | −0.152*** | −0.165** |
| | | | | | (0.038) | (0.092) |
| number of matriculated adults | | | | | 0.131* | 0.203 |
| | | | | | (0.092) | (0.168) |
| number of children | | | | | 0.070*** | 0.063*** |
| | | | | | (0.027) | (0.026) |
| number of elderly | | | | | −0.079*** | −0.092*** |
| | | | | | (0.016) | (0.011) |
| father employed | | | | | −0.436*** | −0.429* |
| | | | | | (0.088) | (0.262) |
| mother employed | | | | | 0.056*** | 0.185* |
| | | | | | (0.015) | (0.127) |
| matriculated * late cohort | | | | | | −0.519*** |
| | | | | | | (0.029) |
| no lag in progression * late cohort | | | | | | −0.164*** |
| | | | | | | (0.035) |
| number of adults * late cohort | | | | | | −0.016 |
| | | | | | | (0.082) |
| number of matriculated adults | | | | | | −0.116* |
| | | | | | | (0.081) |
| father employed * late cohort | | | | | | 0.076 |
| | | | | | | (0.194) |
| mother employed * late cohort | | | | | | −0.248* |
| | | | | | | (0.153) |
| community B | 0.005*** | 0.008*** | 0.008*** | 0.007*** | 0.010* | 0.009 |
| | (0.000) | (0.002) | (0.002) | (0.002) | (0.006) | (0.009) |
| female × months | 0.003 | 0.000 | 0.001 | 0.002*** | 0.006*** | 0.008*** |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) | (0.000) |
| late × months | | 0.006*** | 0.005*** | 0.005*** | 0.005*** | −0.012*** |
| | | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) |
| leaving year unemployment/population | | −0.335*** | −0.377*** | −0.206*** | −0.298*** | −0.250*** |
| | | (0.046) | (0.016) | (0.062) | (0.008) | (0.099) |
| matriculated × months | | | 0.007* | 0.008** | 0.010** | 0.003 |
| | | | (0.004) | (0.005) | (0.005) | (0.013) |
| no lag in progression × months | | | | −0.010*** | −0.014*** | −0.019*** |
| | | | | (0.004) | (0.001) | (0.005) |
| number of adults × months | | | | | 0.005*** | 0.005*** |
| | | | | | (0.000) | (0.000) |
| number of matriculated adults | | | | | −0.005*** | −0.005*** |
| | | | | | (0.001) | (0.001) |
| number of children × months | | | | | −0.003*** | −0.002*** |
| | | | | | (0.000) | (0.000) |
| number of elderly × months | | | | | 0.002*** | 0.002*** |
| | | | | | (0.001) | (0.001) |
| father employed × months | | | | | 0.008** | 0.012** |
| | | | | | (0.004) | (0.006) |
| mother employed × months | | | | | −0.011*** | −0.011** |
| | | | | | (0.004) | (0.005) |
| matriculated × months | | | | | | 0.009 |
| | | | | | | (0.007) |
| no lag in progression * late cohort × months | | | | | | 0.011 |
| | | | | | | (0.010) |
| number of adults * late cohort × months | | | | | | 0.003* |
| | | | | | | (0.002) |
| number of matriculated adults | | | | | | 0.001*** |
| | | | | | | (0.000) |
| father employed * late cohort × months | | | | | | −0.015*** |
| | | | | | | (0.000) |
| mother employed * late cohort × months | | | | | | 0.005*** |
| | | | | | | (0.001) |
| logL | −3361 | −2762 | −2755 | −2751 | −2736 | −2731 |
| Wald test | 0.000 | 0.000 | 0.000 | 0.000 | 0.411 | 0.998 |
| Score test | 0.397 | 0.003 | 0.000 | 0.000 | 0.000 | 0.000 |
| events | 612 | 519 | 519 | 519 | 519 | 519 |
| n | 650 | 556 | 556 | 556 | 556 | 556 |

Note: See footnotes of TABLE 15.

# Appendix B First employment duration

TABLE 17: First employment duration up to 3 years

| covariates | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| (female = 1) | −0.195** | −0.171** | −0.138* | −0.150* | −0.115 | −0.125 |
| | (0.084) | (0.095) | (0.091) | (0.100) | (0.092) | (0.102) |
| unemployment duration (months) | −0.023*** | −0.026*** | −0.032*** | −0.034*** | −0.032*** | −0.035*** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| community B | 0.156** | 0.213** | 0.241*** | 0.273*** | 0.209** | 0.215** |
| | (0.088) | (0.098) | (0.096) | (0.105) | (0.100) | (0.109) |
| matriculated | | | 0.146* | 0.226** | 0.089 | 0.173* |
| | | | (0.102) | (0.119) | (0.106) | (0.123) |
| late cohort | | | −0.117 | −0.156* | −0.120* | −0.172** |
| | | | (0.091) | (0.101) | (0.092) | (0.103) |
| no lag in progression | | | 0.087 | 0.082 | 0.090 | 0.094 |
| | | | (0.099) | (0.107) | (0.098) | (0.108) |
| leading average U/population | | | 2.809 | 1.344 | 3.122 | 0.661 |
| | | | (4.769) | (5.272) | (4.830) | (5.425) |
| number of adults | | | | | 0.002 | −0.030 |
| | | | | | (0.030) | (0.036) |
| number of matriculated adults | | | | | 0.099** | 0.166*** |
| | | | | | (0.058) | (0.068) |
| number of elderly | | | | | −0.011 | −0.058 |
| | | | | | (0.072) | (0.084) |
| n | 466 | 466 | 373 | 373 | 373 | 373 |
| events | 401 | 401 | 314 | 314 | 314 | 314 |
| AIC | 2748 | 2740 | 2197 | 2196 | 2199 | 2195 |
| logL | −1369 | −1364 | −1090 | −1088 | −1087 | −1085 |
| distribution | W | gΓ | W | gΓ | W | gΓ |

Note: *, **, *** show statistical significance at 10, 5, 1%, respectively. Clustered standard errors are shown in parenthesis. Wald tests and score tests are run against the null of all covariates are zero. Events are counts of end of spells. *n* is sample size. shape, scale are weibull parameters, mu, Q, sigma are generalised gamma parameters.

TABLE 18: First employment duration up to 4 years

| covariates | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| (female = 1) | −0.293*** | −0.250*** | −0.199** | −0.190* | −0.160* | −0.153 |
| | (0.094) | (0.106) | (0.106) | (0.118) | (0.109) | (0.120) |
| unemployment duration (months) | −0.023*** | −0.025*** | −0.030*** | −0.031*** | −0.030*** | −0.031*** |
| | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| community B | 0.220** | 0.306*** | 0.266*** | 0.362*** | 0.235** | 0.314*** |
| | (0.095) | (0.109) | (0.112) | (0.129) | (0.115) | (0.129) |
| matriculated | | | 0.105 | 0.202* | 0.046 | 0.135 |
| | | | (0.117) | (0.140) | (0.122) | (0.143) |
| late cohort | | | −0.185* | −0.285** | −0.203** | −0.317** |
| | | | (0.120) | (0.138) | (0.122) | (0.139) |
| no lag in progression | | | −0.044 | −0.053 | −0.034 | −0.049 |
| | | | (0.111) | (0.125) | (0.112) | (0.126) |
| leading average U/population | | | 6.441 | 5.942 | 7.148 | 5.852 |
| | | | (6.850) | (7.659) | (6.916) | (7.754) |
| number of adults | | | | | −0.013 | −0.041 |
| | | | | | (0.037) | (0.040) |
| number of matriculated adults | | | | | 0.103* | 0.167** |
| | | | | | (0.068) | (0.076) |
| number of elderly | | | | | 0.032 | 0.015 |
| | | | | | (0.085) | (0.098) |
| n | 363 | 363 | 277 | 277 | 277 | 277 |
| events | 325 | 325 | 243 | 243 | 243 | 243 |
| AIC | 2339 | 2331 | 1816 | 1814 | 1819 | 1815 |
| logL | −1165 | −1159 | −899 | −897 | −898 | −894 |
| distribution | W | gΓ | W | gΓ | W | gΓ |

Note: *, **, *** show statistical significance at 10, 5, 1%, respectively. Clustered standard errors are shown in parenthesis. Wald tests and score tests are run against the null of all covariates are zero. Events are counts of end of spells. *n* is sample size. shape, scale are weibull parameters, mu, Q, sigma are generalised gamma parameters.

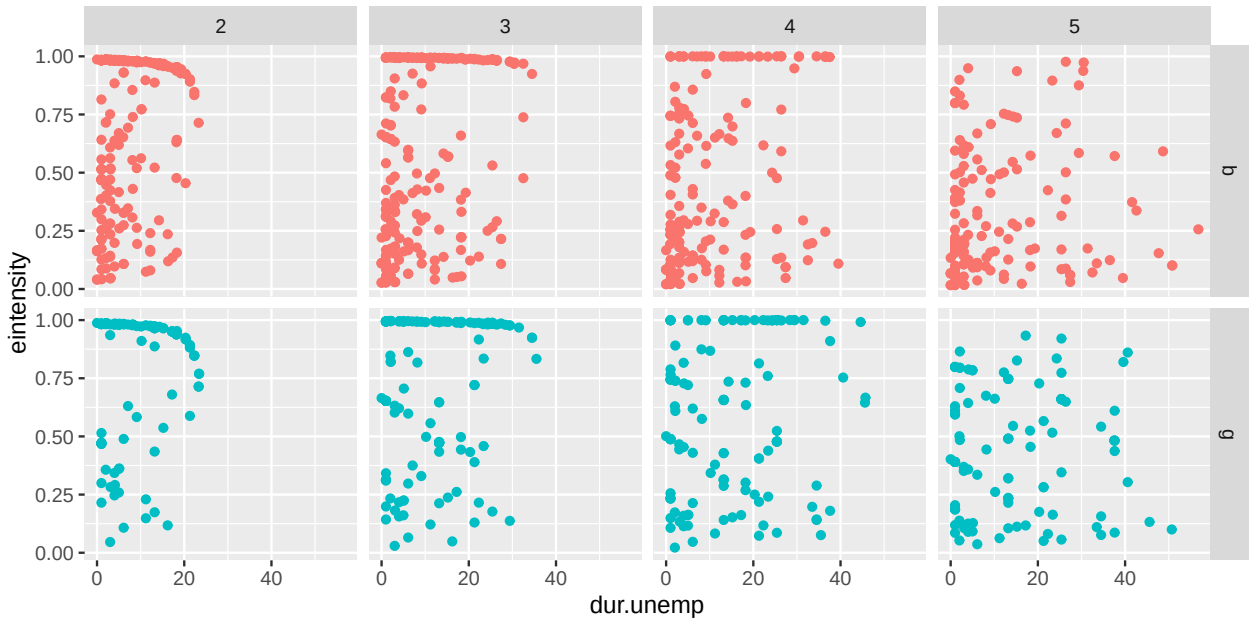


Figure 6 Initial unemployment duration and subsequent employment intensity

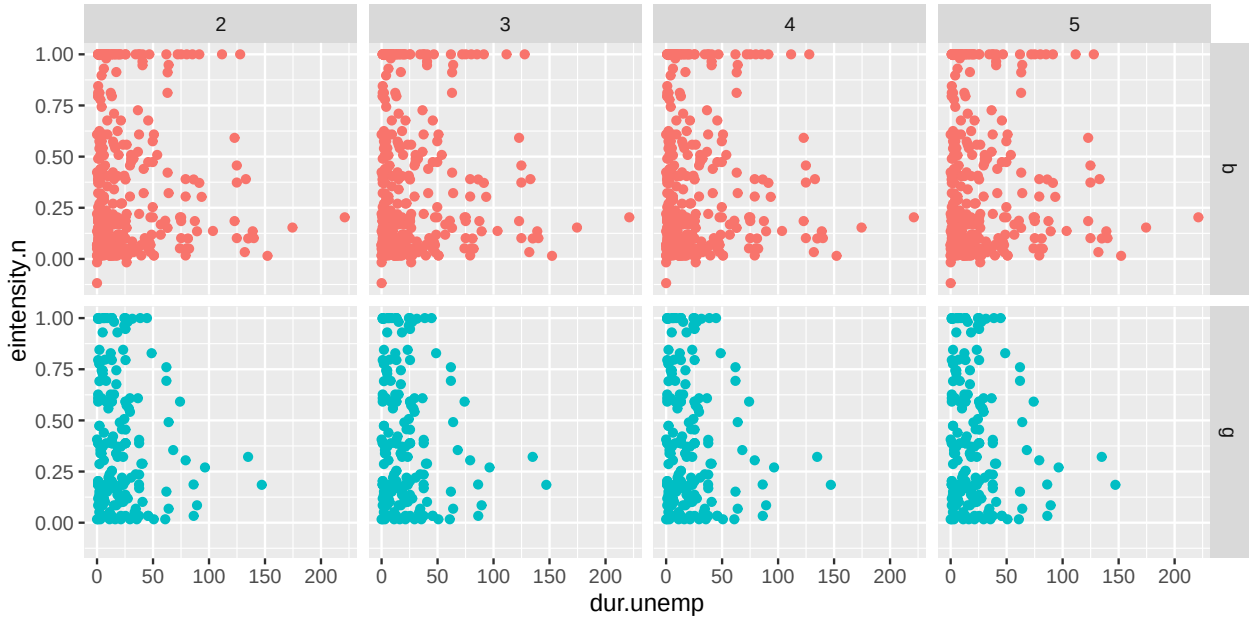


Figure 7 Initial unemployment duration and subsequent employment intensity after up to 5 years

# Appendix C Employment intensity

In Figures 6 and 7, we tabulated scatter plots between initial unemployment duration and subsequent employment intensity, for 2 to 5 years after leaving school for the former and for 2 to 5 years after ending the initial unemployment for the latter. It is hard to see any correlation between initial unemployment duration and subsequent employment duration in both figures.

We will normalise the remaining duration as a measure of employment intensity by forming a

ratio of cumulative employment duration to total remaining duration up to $t$ years.

$$e_{r,t} = \frac{\text{sum of employment duration between } r \text{ and } t}{t - r}.$$

$e_{r,t} \in [0, 1]$. For an individual who has never worked in the first $t$ years after leaving school, $e_{r,t} = \frac{0}{t} = 0$. However, one cannot measure the association between initial unemployment spell and subsequent employment, because unemployment spell is never finished. So we must drop these observations from the analysis, resulting in $e_{r,t} \in (0, 1]$. $e_{r,t}$ may still suffer from an overevaluation of employment that, longer the initial unemploymen $r$, more likely the employment intensity to be close to 1 in the remaining period after the transition to employment.

Table 19 shows the estimated results for $e_{r,t}$ for $t = 2, \ldots, 5$. It shows a large positive relationship between initial unemployment duration and subsequent employment intensity. This positive relationship is not surprising if a longer initial unemployment spell is associated with more preferable job opportunities. matriculated is positively associated with employment intensity, while being in a late cohort and having lagged progression reduces it. These estimates can extend the interpretation that better educational qualification is associated with not just shorter initial unemployment spells but also with subsequent jobs. Estimates on number of matriculated adults are positive and become statistically significant after 3 years. This suggests the long-term benefits in finding jobs by having better qualified adults in the same household, due probably to better home teaching and/or better job network.

The positive relationship with initial unemployment spell is consistent with an arithmetic relationship that a longer initial spell reduces the chance of being unemployed again. To examine if it is a spurious correlation, Table 10 uses $e_{r,r+m}$ as a regressand. The estimates on duration of unemployment now become all statistically insignificant. This implies that strong positive results that we obtained in Table 19 are mostly due to spurious correlations that a shorter remaining period is neccessarily associated with higher employment intensity. Results of other covariates are qualitatively different except for matriculated, late cohort, and number of matriculated adults. male, number of elderly are no longer statitiscally significant.

TABLE 19: Employment intensity up to 5 years

| | After 2 years | | | After 3 years | | | After 4 years | | | After 5 years | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| covariates | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| (Intercept) | 0.466*** | 3.255*** | 2.837*** | 0.172*** | 1.755*** | 1.106 | −0.241*** | 0.321 | 0.022 | −0.744*** | 0.641 | 0.263 |
| | (0.068) | (0.520) | (1.062) | (0.008) | (0.509) | (0.994) | (0.074) | (0.908) | (1.009) | (0.092) | (0.652) | (0.967) |
| unemployment duration (months) | 0.107*** | 0.099*** | 0.099*** | 0.038 | 0.037 | 0.036 | 0.061** | 0.063** | 0.060*** | 0.046*** | 0.062*** | 0.060*** |
| | (0.028) | (0.012) | (0.011) | (0.042) | (0.032) | (0.032) | (0.027) | (0.028) | (0.023) | (0.019) | (0.020) | (0.019) |
| unemployment duration (months)2 | −0.003*** | −0.002** | −0.002*** | 0.000 | 0.000 | 0.000 | −0.001** | −0.001** | −0.001** | −0.001*** | −0.001*** | −0.001*** |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.000) | (0.000) | (0.000) | (0.000) |
| (female = 1) | −0.403*** | −0.421*** | −0.392*** | −0.405* | −0.420* | −0.386 | −0.493 | −0.369 | −0.311 | −0.316 | −0.241 | −0.193 |
| | (0.081) | (0.053) | (0.090) | (0.250) | (0.278) | (0.357) | (0.383) | (0.369) | (0.400) | (0.356) | (0.374) | (0.392) |
| community B | 0.645*** | 0.610*** | 0.562*** | 0.528*** | 0.507*** | 0.484** | 0.376*** | 0.417*** | 0.348*** | 0.414*** | 0.428*** | 0.366*** |
| | (0.017) | (0.079) | (0.192) | (0.001) | (0.097) | (0.232) | (0.024) | (0.055) | (0.115) | (0.023) | (0.023) | (0.031) |
| matriculated | | 0.839*** | 0.763*** | | 0.619*** | 0.520*** | | 0.377*** | 0.259*** | | 0.490*** | 0.367*** |
| | | (0.258) | (0.175) | | (0.112) | (0.195) | | (0.074) | (0.090) | | (0.049) | (0.020) |
| late cohort | | −0.559*** | −0.583*** | | −0.654*** | −0.701*** | | −0.588* | −0.639* | | −0.087 | −0.141* |
| | | (0.177) | (0.205) | | (0.269) | (0.295) | | (0.415) | (0.404) | | (0.135) | (0.095) |
| no lag in progression | | −0.077 | −0.077 | | −0.121 | −0.113 | | −0.130 | −0.129 | | 0.148** | 0.155** |
| | | (0.129) | (0.105) | | (0.248) | (0.229) | | (0.130) | (0.138) | | (0.075) | (0.070) |
| leading average U/population | | −20.543*** | −18.637*** | | −10.683*** | −7.800* | | −3.947 | −1.627 | | −12.775*** | −9.322* |
| | | (4.792) | (5.853) | | (3.999) | (5.262) | | (7.630) | (7.202) | | (4.253) | (6.495) |
| number of adults | | | 0.035 | | | 0.060 | | | −0.027 | | | −0.049*** |
| | | | (0.127) | | | (0.130) | | | (0.067) | | | (0.008) |
| number of matriculated adults | | | 0.152 | | | 0.162 | | | 0.217** | | | 0.221*** |
| | | | (0.163) | | | (0.220) | | | (0.104) | | | (0.021) |
| number of elderly | | | −0.011 | | | 0.039 | | | 0.061*** | | | 0.064* |
| | | | (0.116) | | | (0.031) | | | (0.003) | | | (0.041) |
| n | 327 | 282 | 282 | 352 | 301 | 301 | 294 | 240 | 240 | 244 | 192 | 192 |
| AIC | 371 | 321 | 326 | 467 | 388 | 390 | 407 | 337 | 340 | 314 | 257 | 260 |
| deviance [-2*loglik] | 164 | 132 | 131 | 210 | 171 | 168 | 167 | 132 | 131 | 79 | 61 | 60 |

Note: *, **, *** show statistical significance at 10, 5, 1%, respectively. Clustered standard errors are shown in parenthesis. Wald tests and score tests are run against the null of all covariates are zero. Events are counts of end of spells. *n* is sample size. shape, scale are weibull parameters, mu, Q, sigma are generalised gamma parameters.

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