Determinants of Unemployment and Labour Market Transitions of the Youth in Botswana

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Introduction

Botswana is virtually the only country in Africa that has sustained rapid economic growth over an extended period. Since attaining independence in 1966, Botswana has transformed from one of the poorest countries in the world to upper middle-income status. For much of the post-independence period, Botswana has recorded impressive growth rates. Real per capita income grew by more than 7 percent a year, an achievement that puts it on par with Asian Tigers such as Thailand and Korea during this period.

For the most part, the high growth rate was facilitated by mineral wealth, which was carefully invested, in the context of disciplined fiscal and monetary policies. In fact, Botswana has been credited with effective macroeconomic management of the economy that avoided the resource curse (the counterintuitive pattern of countries rich in natural resources that nevertheless experience slow economic growth). The country has also been able to avoid the Dutch disease by managing its exchange rate to avoid significant appreciation, which would have led to some industries declining as a result of the diamond boom.

However, a major challenge that accompanies that mars Botswana’s success story is the coexistence of a weakly diversified economy. As result, the country has a small production base that is characterised by small productive employment opportunities for the population. In the context of economic growth driven by the mining sector (which is capital intensive by nature) and the Government sector, Botswana’s economic development has been accompanied by existence of high levels of unemployment.

In terms of stylised facts, the youth population (Botswana’s youth fall in the ages 15-39, although internationally, the youth fall in the ages 15-24[1]) tends to experience higher unemployment rates than the older population since young people generally have no workplace experience, which makes it difficult for them to obtain jobs. In Botswana, youth unemployment is estimated at 25.2% with female unemployment higher than that of males at 26.9% percent compared to 23.6% percent for males (Statistics Botswana, 2016). To some extent, the high unemployment rate for this particular group is a result of the high school dropout in the country. In the years 2012-2014, a total of 8,051 students dropped out from secondary school, of which 5,031 were females.

Economic theory explains how the aggregates of employment and unemployment are determined by the business cycle of the economy. During the expansionary phase, it becomes relatively easy for every member of the labour force to find jobs. In this case, it can be argued that every member of the labour force, who is without a job, faces a higher probability of being employed. At the same time, for those with jobs, the probability of losing their jobs becomes lower (Kucharski and Kwiatkowski, 2006). The converse of this is true, in the case of the contractionary phase of the business cycle.

[1] For statistical consistency across regions, the United Nations defines the youth as those in this age category (http://www.unesco.org/new/en/social-and-human-sciences/themes/youth/youth-definition/). The study used the age category 15-39 because most of the youth programmes in Botswana cover individuals aged 15-39.

However, the aggregate unemployment rate may also be influenced by worker flows between different labour market states of employment, unemployment and out-of-labour market. Worker flows refer to the transitions of members of the labour force from one labour market state/position to another labour market state. Thus, it is important to analyse the worker flows (or labour market transitions) among these labour market states for two main reasons. One reason is that while aggregate unemployment may be due to lack of job expansions in the economy, some of the unemployment arise due to job mobility (i.e., transitions of workers from job to job (see Bosler and Petrosky-Nadeau, 2016). In this regard, the larger the magnitudes of the transitions, the greater will their influence be on the aggregates of employment and unemployment. For example, large flows from employment to unemployment will result in a decrease in employment on one hand, and a rise in unemployment on the other. Similarly, large flows from unemployment status (those actively seeking a job) to out-of-the labour market (those not actively looking for a job) would result in a decrease in unemployment. Lastly, large flows from out-of-the labour market to either the unemployment pool or the employment positions would result in increases in these aggregates. The other reason, interconnected with the first reason, relates worker flows to labour market flexibility. The larger the magnitudes of worker flows, the greater the fluidity of the labour market.

While the business cycle position of the economy determines the labour market transitions of the labour force, the socio-economic characteristics of individuals concerning their gender, level of education, type of skill, and age play an important role. These individual characteristics influence the flows of people into different labour market positions, which can be measured by probabilities of losing jobs and probabilities of finding new jobs. This paper seeks to empirically investigate how the socio-economic characteristics of the youth of Gabane village (as well as labour market conditions such as workers wage and government labour market programmes) influence their transitions among the three labour market positions. The transitions are measured in terms of the Markov transition probabilities and the multinomial logit model.

Many studies that were carried out on youth unemployment and on unemployment in general in Botswana did not examine the gross transitions and the transitions determined by individual socio-economic characteristics. Ama (2008) did a study on the transition from higher education to employment by graduates of faculty of Social Sciences in the University of Botswana. The study among other things wanted to find out the graduates' average waiting time to secure their first employment and the extent to which the jobs held were appropriate to the level of education attained. Even though the study was about transitioning from one labour market state to the other it failed to determine the socio-economic characteristics of the graduates that influence that transition, and this is a gap which this study seeks to fill. Kemiso and Kolawole (2017) assessed the factors contributing to rural youth unemployment in the Okavango Delta, Botswana. Specifically, they analyzed the socio-economic and institutional factors (age, education, training etc.) influencing rural youth unemployment in the study area. Again this study, did not examine how the socio economic factors of the youth affected their transition from one labour market position to another. Last but not least, another study on youth unemployment in Botswana is by Diraditsile & Nthomang (2015) who just focused on identifying the strengths and challenges of past efforts aimed at addressing youth unemployment, with a view to develop more effective and relevant interventions to tackle the problem.

This study will contribute to existing literature because there is no literature on labour market transitions in Botswana

Empirical analysis of labour market transitions for the Gabane village youth is enabled by the Community-Based Monitoring Study (CBMS) data that has been collected by the team through the sponsorship of the Partnership for Economic Policy under the CBMS Philippines. The CBMS data provides detailed micro data that shows worker flows among the labour market positions from the perspective of workers, not of employers. Data were collected using tablet based questionnaires and were entered and processed using STATA software. Theme topic research questions were introduced into the standard CBMS questionnaire to capture the labor market states of individuals for the two periods of Jan-Jun2016 to Jan-Jun2017 as well as in Jul-Dec2016 to Jul-Dec2017.

During the process of data collection the enumerators entered the GPS coordinates to capture the location of the household being interviewed. This was a cross sectional study.

The dataset provides a great opportunity that allows investigation of the magnitude of the transitions in the cross section of the population. Notably, the micro dataset allows examination of gross transitions (transitions of persons, regardless of their individual characteristics) and the transitions determined by individual socio-economic characteristics.

Literature Review

In this section, we first look at a brief theoretical literature. The review is useful in providing understanding on the importance of analyzing the transitions of persons across the labour market states, and the appropriateness of analyzing the transitions in terms of the Markov chain process and the Multinomial logit model.

The empirical literature then reviews some of the past studies that employed the same methods of analysis and presents their main findings, for comparative analysis. Notably, emphasis is placed on results relating to the impact of socio-economic characteristics of individuals – such as gender, level of education, type of skill, and age on people's outcomes in the transition from one labour market state/position to another labour market state.

Theoretical literature Review

As already stated, although aggregate unemployment rate may be due to structural problems (e.g., inadequate creation of job opportunities) in the economy, it can also be influenced by worker flows between different labour market states of employment, unemployment and out-of-labour market. Thus, it is important to analyse the transitions of persons across the labour market states, as they have policy implications. To the extent that unemployment results mainly from high turnover (which, in this study, can be associated with high worker mobility across different states), the necessary policies would be those geared to improving information on labour market conditions to the unemployed, in order to expedite their chances of getting new jobs. However, in the case where unemployment is characterised by high persistence (which, in this study, can be associated with no movement from one labour market state to another between the two periods – i.e., January-June 2016 versus January-June 2017 and July-December 2016 versus July-December 2017), required policies are more of the structural type, including suitable training, job-creation schemes and income-support schemes (see Arif *et al.*, (no date)).

Studies conducted on individual labor market dynamics have utilised duration models, binary logit/probit models and/or multinomial logit models, as well as studies that model individuals' transitions among some labor force states as a Markov chain process. Majority of the studies that employed duration models attempted to estimate the duration of unemployment, conditional on individual personal characteristics and labor market conditions experienced by individuals.

Studies that use multinomial logit (MNL) model consider that such a model is suitable in the context of a qualitative dependent variable, where the dependent variable comprise more than two categories that are not ordered – as is the case with labour market positions of employment, unemployment and out-of-labour market (see, for example, Bukowski and Lewandowski, 2005; Kucharski and Kwiatkowski, 2006). The MNL model can be used to estimate the risk that a particular labour market position/state can be realized (see Kucharski and Kwiatkowski, 2006; and Fabrizi and Mussida, 2009). In addition, by estimating the multinomial function, the probability that a certain event will occur can be quantified, as determined by the individual 'worker' characteristics (e.g., age, education, etc) and other factors. It is noted that the use of the multiple regression model to analyse the effect of covariates on the probabilities is crucial to obviate the potential for misleading results due to a third variable effect from the bivariate relationships entailed in the transition matrix probabilities. For example, the transition probabilities associated with the age of individuals may be mainly due to the effect of another variable, not necessarily the age factor.

Another strand of literature entails studies that assess labour market mobility by developing matrices which capture the movement of persons across labour market states (see, for example, Foley, 1997, Fabrizi and Mussida, 2009, Arif *et al.*, (no date)). Transitions across labour market states indicate the extent of mobility of workers/persons in the labour market. The greater the probability of transition from one labour market state to another, as opposed to the probability of remaining in the same state as in the previous period, the higher the mobility of workers in the labour market. The greater the probabilities of remaining in the same labour market state in the current period, alongside small probabilities of transition between labour market states, the more inflexible the labour market is.

The transition probabilities are modelled using the Markov chain model, which can be described as follows. Let be a random variable representing the position of an individual in the labour market at time . In this paper, is a discrete random, with three possible values (employment, unemployment, and out-of-labour market). Since the individuals' transitions are observed only at discrete time points and exact transition dates are not available, then it is appropriate to use a first-order Markov chain process for this study's data. A first-order discrete Markov chain is given by

$$(\quad = | \quad , \ldots , \quad) = (\quad = | \quad)$$

Where the index $= 1, \ldots$, stand for the labour market states.

In this context, the probability of transitioning from state to state between time -1 and period depends only on the immediate past value, implying that the process has no long memory (for details, see Fabrizi and Mussida, 2009). Given the three labour market positions assumed in this study, then nine probabilities can be calculated. These probabilities give the probability transition matrix, $( ) = \quad ( )$. Often the literature axiomatically assumes that the transition probabilities are independent of time, a concept referred to as time-homogeneity of transition probabilities. The time-homogeneity assumption is reasonable if the cross-sections used in the study entail a short period of time.[2]

Empirical literature Review

Several studies empirically examined the transitions probabilities of workers across various labour market positions in different countries.

Steiner and Kwiatkowski (1995) presented an empirical analysis of the labour force dynamics in Poland in the period May 1992 – February 1993 after it transitioned to a market economy. Transitions between employment, unemployment and non-participation in the labour force at the individual level were derived from panel data and made use of the microdata of the quarterly (92/II, 92/III, 92/IV, 93I) Polish Labour Force Survey. These transitions were related by means of a dynamic microeconomic model – Markov Model of individual labour force transitions- to various demographic and socio-economic characteristics of the labour force, labour market indicators and other structural variables. The sets of explanatory variables taken into account in the estimation of the various transition models comprised of individual and household characteristics (age, disability, education, marital status and for females, children by age group), various labour market indicators (type of region, urban agglomeration and the regional unemployment rate) and time dummies which accounted for changes in general labour market conditions associated with the economic transition process as well as for seasonal effects, and other variables (Steiner and Kwiatkowski, 1995).

Quarterly empirical transition rates between labour force states (in %), May 1992 to February 1993, except for the transition rate from employment to unemployment all rates have declined between 92I to 93I. The transition rate from employment into non-participation was much higher than into unemployment rate in the first two periods, but dropped below the level of the later in

[2] This assumption is applicable in the case of the data used in this study, which involves only two years.

the last period. This seemed to reflect the wide-spread use of early retirement schemes as a means of labour force adjustment rather than just seasonal factors. Resulting in the outflow rate from employment in the last period was substantially lower than at the beginning of the observation period. The reduction of the outflow rate from unemployment over the observation period is mainly due to the drop in the transition rate into employment in the last quarter. The transition rate from non-participation into employment as well as into unemployment, and hence, the outflow rate from non-participation declined substantially over the observation period (Steiner & Kwiatkowski, 1995)

Foley (1997) used information contained in a nationally representative longitudinal survey of Russian citizens to analyse the labour market behaviour of individuals from 1992 to 1996 during the transition to a market economy. Under Markovian assumptions, the pattern of transitions between labour markets were identified. Results indicated that the probability of losing a job increased by 75 percent from 1992 to 1996 while the re-employment probability declined by 24 percent, leading to an increase in long-term unemployment. He also found out that education is a factor in exiting unemployment to a job, by 1995-96 individuals with higher, special secondary, or ordinary secondary education were more likely to find employment than those with primary education or less. University or graduate degrees carry the greatest weight, increasing re-employment probability by 27.5 percentage points.

In Van der Merwe's (2016) empirical study, the objective was to understand how someone's characteristics and circumstances affect the probability of being in a particular labour market state in the next year. Van der Merwe considered four mutually exclusive labour market states which were employed; unemployed; marginally attached to the labour force; and out-of-labour force. She examined individual changes in labour market status from year to year by using one-year-ahead transition probabilities. She found that more than 40 percent of individuals who were unemployed in one year typically became employed in the following year. Furthermore, among those who were employed in each year, over 90 percent remained in employment in the next year. The results for transitions into the other three labour market states also showed that an individual's labour market status is unlikely to change from one year to the next.

To unravel the relative importance of individual characteristics associated with an individual's future labour market status, a more formal modelling approach was required. A multinomial logit framework was used as individuals could be in one of four mutually exclusive labour market states stated above. The multinomial logit model allows the dependent variable to take on multiple discrete values. The results revealed that being female increases the probability of being outside the labour force in the next year by around 1.4 percentage points. The result was in line with the aggregate data that consistently showed that a higher proportion of women were outside the labour force than men in Australia in any given year. This was possibly due to earlier retirement or family responsibilities. She also established that having a degree or diploma (compared with finishing high school), increases the probability of being employed in the next year by around 1 percentage point and lowers the probability of being unemployed in the next year by around ½ percentage point. In contrast, incomplete schooling (compared with finishing high school) reduced the probability of becoming employed by almost 3 percentage points and increases the probability of becoming unemployed or moving out of the labour force in the next year. These results were consistent with the notion that higher levels of human capital accumulation increase the probability of being employed in the future. In terms of age, Van der Merwe (2016) that older individuals were more likely to be outside of the labour market than younger individuals, although the proportion had been gradually declining over the past decade.

Van der Merwe (2016) also established that the migrant status of an individual affect his transition from one labour market state to another. They found out that Compared with being born in Australia, being a migrant from a non-English-speaking background reduces the probability of being employed in the next year by 2 percentage points, regardless of the person's current labour market state, while being a migrant from an English-speaking background reduces the probability by only 0.7 percentage points. This implies that migrants from a non-English-speaking background are less likely to find employment owing possibly to language barriers. She also found out that living in a city, compared with regional and rural areas, increases the probability of being employed in the next year by around 0.75 percentage point and last but not least they discovered that the presence of a long-term health condition reduces the probability of being employed in the next year by around 3.5 percentage points and it had the largest negative effect (Van der Merwe, 2016)

Audas *et al* (2005) empirically examined labour market transitions in Hungary. Specifically they wanted to determine the factors that predict individuals' being unemployed in a month as opposed to working, studying or serving in the military. To do this they estimated a probit model looking at the initial labour market outcome (1 if unemployed; 0 otherwise). They found out that, with regards to gender, females tend to be considerably more likely to be unemployed compared to their male counterparts. They also found out that school type and education performance are both significant predictors of being unemployed. Individuals who do well on their matriculation examinations tend to be much less likely to be unemployed, reflecting that they are more inclined to remain in education(out of labour force), while those who do poorly look for work and often end up experiencing unemployment. Lastly, they established that older members in the sample were more likely to be unemployed than their younger counterparts. This was mainly due to older graduates not wanting to participate in lengthy higher education courses and instead choosing to seek employment, making them much more disposed to an initial spell of unemployment.

Fabrizi and Mussida (2009) investigated the determinants of labour market transitions in Italy. They applied a Markov chain approach and multinomial logit model to individual-level data from the 1993-2003 labour force surveys in Italy. They examined the labour market transitions between the states of employment, unemployment, and inactivity. Their results showed that being male reduces the probability of leaving the labour force. In other words females were more likely to leave the labour force compared to males. This reflects a differential between the behaviour of males and females into the labour market, signalling the existence of a discouragement effect for women or the fact that women have more family responsibilities compared to men. They also established that having a degree increases the likelihood of leaving unemployment with respect to somebody with a diploma or who only attended compulsory education. But it did not seem to affect the likelihood of exiting the labour force. Lastly it was found out that getting older reduces the likelihood of leaving the labour force. This may be because, the greater the age, the greater the responsibilities hence one would be less likely to exit the labour market.

Fabrizi and Mussida (2009) also found that being married accelerated the probability of leaving the labour force. Work experience was found to accelerate the exit from the state of unemployment. Family size did not have any effect on the transitions from one labour market state to another.

Kavuma, *et al* (2015) examined the flow of workers between employment states, the role of education in these transitions and the impact of the transitions on earnings. They used panel data for three waves (2005/06, 2009/10 and 2010/11) of household surveys in Uganda. Using the Markov chain process, they estimated transition probability matrices and found bi-directional transitions between formal and informal employment but with a higher tendency of workers to transition from formal to informal than in the opposite direction. When they investigated the relationship between education and transitions using probit models, they found that the transition from informal to formal increases with education but the movement from formal to informal employment and switching from not working to working declines with education.

Tasci and Tansel (2005), using Household Labor Force Survey panel data of 2000 and 2001 computed Markov transition probabilities by gender, marital status and rural-urban residence for three labor market states: employment, unemployment and not in labor force. Moreover, they carried out multinominal logit regressions. Some of their major findings are as follows: For the urban women, while the probability of moving from unemployment to employment is lower than urban men, the probability of moving from employment to unemployment is higher, which leads to higher unemployment rate for women. The probability of losing the job decreases with education.

Voicu (2002) used micro data from the Romanian Labor Force Survey to study individual labor market histories and estimated the effects of personal characteristics on individuals' labor market decisions during the transition process. A multivariate probit model was used as empirical specification of the individual employment decisions. The results showed that women had lower employment probabilities in all years, for all ages and educational categories. High education and high levels of specific skills helped individuals maintain high employment probabilities for longer periods of time. Workers with ages at the two ends of age range had higher probabilities of both entering and leaving employment.

To quantify the magnitude of transitions across occupational categories, Cuesta and Bohorquez (2011) used a panel of households representative of the main metropolitan areas in Colombia over the period 2008- 2009. Results showed that transitions between occupations are large and asymmetric; they are disproportionally more likely to happen from formal to informal occupations than vice versa. It is reported that such transitions are also different for salaried workers compared with the self-employed, as well as by poverty status of the worker. Salaried workers are more likely to transition first into other salaried jobs, while self-employed are more likely to transition into unemployment or out of the labor force.

Synthesis of the empirical literature review (A critical review)

In explaining unemployment and transitions in the different labour markets, most studies computed the transition probabilities between the labour market states of employment, unemployment and out-of-labour force under Markovian assumptions. Then presented multinomial logit models to analyse the determinants of labour market states; Seyit (2015), Van der Merwe (2016), Tasci (2005), Fabrizi (2008). Most studies determined transition probabilities by gender, age, education groups, occupation and marital status (Seyit, 2015), Tasci (2005). However, Kavuma (2015) estimated conditional transitional probabilities using the Markov chain process & probit models, and included three transitions: transitions from “not working” to “working” (either formal or informal), transitions from formal to informal employment, transitions from informal to formal employment. Whereas, Audus (2005) examined the nature of transition from school to work transition in transition economies to a market economy.

In examining and comparing labour market dynamics, in most studies, panel data was used, (Kavuma, 2015), (Tasci, 2005), (Bosch, 2007),as the panel feature on the surveys makes it possible to measure the changes between successive quarters and years and also because panel survey is said to provide detailed information on the employment status, social security coverage, demographic characteristics, working hours, labour and income, living conditions, job characteristics & socio-economic conditions of the subjects (Seyit, 2015). Whereas, some studies used the longitudinal data, (Fabrizi, 2008), (Audus ,2005) and Van der Merwe (2016) as it collects information from individuals and households about economic and subjective wellbeing, labour market dynamics and family dynamics, allowing for labour market flows estimation and valuable analysis of the labour mobility.

The choice of the time span or period of the researches on mobility analysis was based on different factors, for example, Seyit (2015) and Tasci (2005) conducted the study after the economic and financial crisis which had great repercussions on the labour markets. So, they examined labour market reforms, to study if the policy measures helped in alleviating the adverse effects of the crisis on the labour market by analysing worker transitions across different market states. Audas (2005) noted a major policy concern in the transition economies which has been accompanied by the rapidly rising levels of unemployment since the introduction of market systems. Fabrizi (2008), investigated some of the changes which occurred in the labour market, which allowed for the evaluation of the feasible impacts of the labour market regulations introduced through the decade and data availability.

Most of the studies on labour market transitions covered a wide age group of 14/15 to 64/65 years (Cilasun, 2015), (Fabrizi, 2008) and (Kavuma, 2015), (Tasci, 2005). Whereas a few of the studies took recognition of the fact that most of the population consists of young people and observed that the length of school to work transition is increasing, (Audas, 2005), (Elder, 2014), therefore they focused their research on the young population.

With regard to findings, variables such as age, gender and education have the same sign, that is to say, the way in which these variables affect labour market transitions is the same whether one is in a developing country or a developed country. There are some variables such as family networks, health status, work experience, family size, and migrant status, among others that affect labour market status transitions but are not widely used in the literature. They carry different signs depending on the labour market conditions prevailing in the country that the study is conducted.

Worth noting is that there is limited research on unemployment and labour market transitions in Africa and very few studies focus on youth, which is mostly affected by unemployment. Interestingly, most of the empirical literature on this topic has not included government labour market programmes in their analysis, as is done in this study.

This study will first model individual's experiences using Markov transition probabilities. However, due to the limitations of this approach – in that transition probabilities can only be observed in the context of bivariate relationships, the multinomial logit model is then used to quantify the probability of transition from one labour market state to another, which allows for the confluence of multiple variables.

Data and Methodology

To obtain the micro data used in this study, the CBMS survey tool was modified to capture changes in the labour states of respondents over two time periods (January-June 2016 and July-December 2016 versus January-June 2017 and July-December 2017). In each period, the theme topic questionnaire asked the youth aged 15-39 years for their employment status, and whether they participated in government intervention programmes, as well as the specific type of government programme they participated in. Meanwhile, the information on the individual characteristics of the respondents (such age, gender, educational qualification, etc), was obtained in terms of the standard CBMS survey instrument.

The first part of the methodology of this study employs the Markov chain model to investigate workers' transition probabilities. At the aggregate level, the labour market transition probabilities can be summarised as in the matrix presented in the following table.

Table 1: Matrix of Labour Market Transition Probabilities over a Period

		Destination		
,	Origin state	Employed	Unemployed	OLF
	Employed	(|)	(|)	(|)
	Unemployed	(|)	(|)	(|)
	OLF	(|)	(|)	(|)

Notes:

1. OLF denotes out-of-labour force.
2. The labour market states are , = { , , }.
3. =employed, =unemployed, and =OLF.

The entries in the cells of the table indicate the probability of transitioning to a particular labour market state in the current period $(\ )$, conditional on the individual having been in a certain state in the previous period $(\ -1)$. For example, $(\ | \ )$ refers to the probability that an individual is unemployed at time , conditional on being employed at time -1.[3]

The second part of the methodology employs the multinomial logit model. The model helps to determine the covariates that have significant impact on the probability of transitioning from one labour market state to another. The model advances on the analysis based on Markov transition probabilities, which basically entail a univariate relationship between a transition and a particular variable of interest, say gender. The multinomial logit model, on the other hand, provides a multivariate analysis of the probability of transitioning between different states. Briefly, the specification of the model goes as follows.

Suppose the i[th] investigated individual faces $= \{1, 2, 3, \ldots, \ \}$ events – where the events are labour market transitions in our case. Thus, the probability that a particular event occurs, (e.g., transition from employment to unemployment), can be obtained by estimating the parameters of a multinomial logit model. The probability that event (say, transition from employment to unemployment) for the i[th] individual will occur equals

$$= \frac{\quad}{\Sigma}$$

where is the probability of transitioning between labour market states; includes the characteristics of the individual (such as age, education, etc.) that are remain identical across the different labour market positions; and are parameters to be estimated.

The fact that the characteristics remain identical for each alternative state in the multinomial logit model allows proper comparison and isolation of the characteristic(s) that is important in determining movement from one labour state (the reference category) to another versus movement from the same reference category another alternative. In addition, given that the individual characteristics do not vary for each alternative labour market state, the probabilities of realizing each labour market state must be normalised with respect to one of them (which would be referred to as the reference category). Thus, the model would then give the probability of transition from the base/reference category to one of the other two labour market states (see Bukowski and Lewandowski, 2005).

[3] Given that a person is allowed to be in only one of the labour market states at a given point in time, then each row of the transition probability matrix must sum to unity (cf. Clark, 1978).

Empirical Analysis of Gabane's CBMS Data: Transition Probabilities

Data Description

The data used in this analysis is taken from a study of Youth Unemployment in Gabane, Botswana. This is a cross sectional study that was conducted to collect data on the employment status of the Youth in the Gabane area. This location was chosen on the basis of the unemployment status of the village during the 2011 Population and Housing Census which was 17.4%, and also because of its proximity to Gaborone, where the research team is based. During the Census period the village has shown to be one of those with high unemployment rate.

Preliminary results

The overall population recorded in Gabane is 6842. The total number of households interviewed is 2693. The data showed that there are more females (56.01%) than males (43.99%) in the study area. Further, it was found that the majority of the population is the youth (15-39 years old) and this was expected. They comprise 55.4% of the total population, followed by those 0-14 years with 22.8%. Table 1 below presents a summarized profile of our selected locality (Gabane village):

Table 2: Profile of Gabane village (Source: Gabane CBMS study)

Profile of Gabane Village	
Total Population	6842
No of households	2693
Youth (15-39years) % of Total Population	55.4%
Unemployed youth (2011 Population and Housing)	17.4%
Unemployed youth (CBMS Study)	23.3%
People living with disability	1.3%
Source: Gabane CBMS Study 2018	

Given that we have provided the profile of Gabane village, we can now consider the labor market status of Gabane village. In particular, we determine the distribution of youth employment status being Employed (These were individuals, who during a specified short reference period, did some work either for payment in cash or in kind (paid employees) or who were in self-employment for profit or family gain as well as persons temporarily absent from these activities but definitely going to return to them (e.g. on leave or sick)., Unemployed (Unemployed persons were those individuals who did not do any work in the past seven (7) days during the study period, and were in the ages 15-39. These are persons who did not work for payment in cash or in-kind, and/or were not in self- employment for profit or family gain, and were demonstrably active in looking for a job in the past 30 days and out-of-labor force (persons are defined by the fact that they do not have a job and are either not actively looking for a job or are not immediately available to work (or both), i.e. they are neither employed nor unemployed. We further observe if there are any structural problems within the labor market. In particular we will look at the proportion of those who are unemployed, employed and out-of-labour force., We also looked at the effects of gender and age on the labour movements across the labour market positions.

Table 3: Distribution of Sample Labor Market States for Gabane Youth

Status	Jan/June 2016		July/Dec 2016		Jan/June2017		July/Dec 2017	
	N	%	N	%	N	%	N	%
Employed	1740	44.7	1703	44.78	1871	49.21	1900	49.97
Unemployed	1556	40.92	1562	41.08	1441	37.9	1426	37.51
Out-of-Labor market	547	14.38	537	14.12	490	12.89	476	12.52
	3803		3802		3802		3802	

The distribution shows a consistent pattern for all states across the four time periods. The period of study is characterised by low employment and high unemployment and out of labor market rates. A large proportion of the sample reported their status as unemployed putting an unemployment proportion to between 37.5-40.9 percent among the youth. The employment proportion was at 44.7 percent in January to June 2016 and slightly rose to just 50 percent in July to December 2017, thereby causing unemployment and out of labor market proportions to decline by 3.41 percent and 1.86 percent respectively during the same period.

A gender breakdown of the labour marker distribution is given in tables 4 and 5 for males and females respectively. As expected, high proportion of unemployment and out-of labor market are found among females than males. These results depict the existing problem in Botswana because generally female employment and participation rates are low (Statistics Botswana, 2018). About 51 percent of males were in employment at the beginning of the study period and the proportion increased to 57.5 percent by end of study period whereas 40 percent of females were in employment in January-June 2016 and there was a lesser increase in the proportionto 44.3 percent in July to December 2017 compared to male employment.

Table 4: Distribution of Sample Labor Market States for Gabane Youth (Males)

Status	Jan/June 2016		July/Dec 2016		Jan/June2017		July/Dec 2017	
	N	%	N	%	N	%	N	%
Employed	836	51.07	833	50.89	919	56.14	941	57.48
Unemployed	580	35.43	589	35.98	515	31.46	503	30.73
Out-of-Labor force	221	13.50	215	13.13	203	12.40	193	11.79
	1637		1637		1637		1637	

Table 5: Distribution of Sample Labor Market States for Gabane Youth (Females)

Status	Jan/June 2016		July/Dec 2016		Jan/June2017		July/Dec2017	
	N	%	N	%	N	%	N	%
Employed	864	39.89	870	40.18	952	43.97	953	44.30
Unemployed	976	45.06	973	44.94	926	42.77	923	42.63
Out-of-Labor force	326	15.05	322	14.87	287	13.26	283	13.07
	2166		2165		2165		2159	

In Tables 6-8, we compute the transition probabilities of individuals as they move across the different labour market states of employment, unemployment and out of labour market to better understand the determinants of youth unemployment across different demographic groups.

Table 6 gives the transition probabilities of the whole cohort during the study period. The transition probabilities inform us on the changes in the employment status of the cohort. For the period January-June 2016 to January-June 2017, we observe the probability of 0.93 that those who were employed remained in that state compared to 0.92 during the period July-December 2016 to July-December 2017. The transition probability of moving from employment to unemployment state was 7.2 percent and it increased to 8 percent in the following period.

Further examination on those who were unemployed and out of labor force in the previous period, there is a transition probability of 18.7 percent and 2.2 percent respectively of moving into employment state. These probabilities increased to 20.4 percent and 3.9 percent respectively in the July-December 2016 to July December 2017 period. During this same period there was slight increase in the movement from unemployment to out of labor market as well as a decrease in those who remained out of the labor market (83.8 percent from 85.6 percent).

Table 6: Transition probabilities for overall sample for the period Jan-June 2016 to Jan-June 2017 and July-December 2016 to July-December 2017

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.933	0.072	0.002
U	0.187	0.8	0.0006
O	0.022	0.122	0.856
State/ period	July-December2016 to July-December 2017		
	E	U	O
E	0.917	0.08	0.003
U	0.204	0.783	0.013
O	0.039	0.123	0.838

In Tables 7 and 8 the transition probabilities were calculated for males and females. Similar patterns of transition probabilities are observed for both males and females to those of the overall sample. The transition probabilities of those who were employed remaining in the employment state were 94.9 percent in the period of January-June 2016 to January-June 2017. This transition probability slightly decreased in the July-December 2016 to July-December 2017 by 0.5 whereas for females the decline was 0.6 percent. About 5% of those who were employed transited to unemployment state during the two periods of study. The decline in the transition probabilities of those who remained unemployed and those who remained out of the labor market in the last period was primarily due to the fact that those males who were unemployed (24.4 percent) and those who were out of the labor market (5.1 percent) moved into employment.

However, among the females the transition probabilities of moving out of employment to unemployment was higher than that of males at 10.2 percent. Further, we observe lower female transition probabilities from unemployment to employment (17.9 percent) and from out of labor market to employment (3.1 percent) respectively in the July-December 2016 to July-December 2017 period. It is evident that females are more likely to lose employment than males and also that males have high employment opportunities than females.

Table 7: Transition probabilities for Males for the period January-June 2016 to January-June 2017 and July-December2016 to July-December 2017

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.949	0.048	0.004
U	0.212	0.772	0.016
O	0.014	0.122	0.864
State/ period	July-December 2016 to July-December 2017		
	E	U	O
E	0.944	0.052	0.005
U	0.244	0.742	0.014
O	0.051	0.107	0.842

Table 8: Transition probabilities for Females for the period January-June 2016 to January-June 2017 and July-December2016 to July-December 2017

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.897	0.102	0.001
U	0.172	0.818	0.009
O	0.028	0.123	0.850
State/ period	July-December 2016 to July-December 2017		
	E	U	O
E	0.891	0.108	0.001
U	0.179	0.808	0.013
O	0.031	0.133	0.835

To further analyse the labor market situation in Gabane, the transition probabilities were calculated for age groups 15-24, 25-34 and 35-39 age groups respectively. For the younger age group, we observe that the transition probabilities of moving from unemployment to employment increased by 2 percentage points from 13.1 to 15.1 percent from the period January–June 2016 to end of July-December 2017. A slight decline in the transition probabilities of moving from employment to unemployment was observed (from 18.5 to 17.4 perfect) coupled with a substantial decline in the transition probabilities of moving from employment to of labor force (and from 11.6 to 1.7 percent) during the same period. Moreover the transition probabilities of moving from unemployment to unemployment and from out of labor force to out of labor force decreased (from 85.3 to 82.8 percent and from 87 to 84.9 percent) respectively during the same period.

Table 9: Transition probabilities for Age group 15-24

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.803	0.185	0.116
U	0.131	0.853	0.162
O	0.162	0.113	0.870
State/ period	July-December2016 to July-December 2017		
	E	U	O
E	0.808	0.174	0.017
U	0.151	0.828	0.203
O	0.029	0.121	0.849

Table 10 depicts the movements of the age group 25-34 years. There is a similar increase in the probability of moving form unemployment to employment (from 24.7 to 25.9 percent). Furthermore, we observed that the probability of moving from employment to unemployment increased as well as the probability of moving from out of labor force to employment (from 7.5 to 8.1 percent and from 7.8 to 12.5 percent) respectively in the period between January–June 2016 to July-December 2017. Surprisingly the probability of remaining out of labor force increased from 70.6 to 72.9 percent in the same period.

Table 10: Transition probabilities for Age group 25-34

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.924	0.075	0.001
U	0.247	0.743	0.010
O	0.078	0.216	0.706
State/ period	July-December2016 to July-December 2017		
	E	U	O
E	0.918	0.081	0.0009
U	0.259	0.731	0.010
O	0.125	0.146	0.729

The labor market transition behaviour of the older group among the youth is shown in Table 11. For the period from January–June 2016 to July-December 2017, there was a substantial increase of 33 percent in the transition probability of moving from out of the labor force to employment. This movement triggered a huge decline in the transition probability of moving out of labor force, 67 percent. On further examination, the probability of movement from unemployment to employment increased from 18.4 to 20.1 percent. This was the one group that experienced high employment rates compared to the other groups. It is not clear whether employers preferred older more experienced workers over the younger less experienced workers.

Table 11: Transition probabilities for Age group 35-39

State/ period	January-June 2016 to January-Jun 2017		
	E	U	O
E	0.958	0.039	0.0018
U	0.184	0.816	0.0
O	0.0	0.0	1.0
State/ period	July-December 2016 to July-December 2017		
	E	U	O
E	0.949	0.049	0.002
U	0.201	0.799	0.0
O	0.33	0.0	0.67

Tables 12-14 give the transition probabilities for the education groups : preschool, primary and secondary. On examining these tables we observe that the probabilities of remaining in employment reduced for these groups during the period under investigation (from 89.5 to 86.5 percent for primary and from 92.3 to 91.7 percent for secondary). Generally there was minimal movement in the secondary group compared to the primary group. Although the probabilities of moving from employment to unemployment increased for the primary level (from 10.5 to 13.5 percent) there was no movement from employment to out of the labor force. It is also observed that there was no movement from out-of labor force to employment. This resulted in the increase in the transition probability of remaining out of labor force from 86.7 to 92.3 percent. The lack of movement from out of labor force shows there could be some discouragement in searching for employment by the primary level group. On the other hand the transition probability of remaining out of labor force decreased from 85.5 to 83.5 percent for the secondary group. This could be argued that the decreased was due to the observed transition probabilities from out of labor force to employment unlike in the primary group.

Table 12: Transition probabilities for Education-Preschool level

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.897	0.102	0.001
U	0.173	0.818	0.009
O	0.028	0.123	0.850
State/	July-December 2016 to July-December 2017		

period	E	U	O
E	0.891	0.108	0.001
U	0.178	0.807	0.013
O	0.031	0.133	0.835

Table 13: Transition probabilities for Education-Primary level

State/ period	January-June 2016 to January-June 2017 E	U	O
E	0.895	0.105	0.0
U	0.154	0.837	0.019
O	0.0	0.133	0.867
State/ period	July-December 2016 to July-December 2017 E	U	O
E	0.865	0.135	0.0
U	0.2	0.782	0.018
O	0.0	0.077	0.923

Table 14: Transition probabilities for Education-Secondary level

State/ period	January-June 2016 to January-June 2017 E	U	O
E	0.923	0.074	0.002
U	0.189	0.799	0.011
O	0.023	0.123	0.855
State/ period	July-December 2016 to July-December 2017 E	U	O
E	0.917	0.079	0.003
U	0.204	0.783	0.013
O	0.04	0.125	0.835

It is common that individuals either through their employer or by themselves enroll for skills development. The transition probabilities were calculated for individuals with training skills to determine if training is a determinant of employment. In Tables 15-16, when we examine the transitions from employment to unemployment from January–June 2016 to Jan-June 2017, we observe that there was 7.4 percent of losing employment while the transition probability of moving from unemployment to employment was 18.7 percent. In general among those who went for training for about 0-2 times, the probabilities of finding a job increased for those who were unemployed and those out of labor market. While the probabilities of remaining unemployed and out of the labor force decreased (from 80.1 to 78.3 percent and from 85.6 to 83.8 percent) respectively during the period under study. However, some interesting results are obtained for the individuals with the opportunity of training 3-5 times. A pronounced 50 percent transition probabilities of moving from unemployment to employment was reflected during the first period of study while the second period of study recorded no activity. Therefore the second period of study showed no job opportunities for those who went for training 3-5 times. This could be that those with skill chose to take up jobs that they are skilled in or it could be that there is a mismatch in the job market

Table 15: Transition probabilities for Training Period: 0-2 times

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.923	0.074	0.002
U	0.187	0.801	0.003
O	0.022	0.122	0.856
State/ period	July-December 2016 to July-December 2017		
	E	U	O
E	0.917	0.079	0.003
U	0.203	0.783	0.013
O	0.039	0.122	0.838

Table 16: Transition probabilities for Training Period: 3-5 times

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.909	0.09	0.0
U	0.5	0.5	0.0
O	0.0	0.0	0.0
State/ period	July-December 2016 to July-December 2017		
	E	U	O
E	0.909	0.09	0.0
U	0.0	0.0	0.0
O	0.0	0.0	0.0

The behavior of job seekers during the time of labor participation is important in the market analysis. Participation in government programs offered employment opportunities for those applied and qualified. About 61.9 percent transition probability of moving from unemployment to employment was realized in the period January-June 2016 to January to June 2017. The opportunity increased to 64.3 percent in the next study period. Surprisingly there were no employment opportunities for those who were out of labor force during the whole study period. There were lower employment opportunities for those who did not participate in government programs, with only 18.2 percent opportunity of moving into employment states from unemployment and 2.2 percent for those moving from out of labor market. These transition probabilities increased to 19.6 and 3.9 percent respectively in the last period of the study. Compared to those who did not participate in programs the risk of losing jobs was high at 15.4 percent and 18.2 percent during the first and second period of the study Those who did not participate in programs experienced lower job losses at 7.5 percent and 8 percent in the first and second period of study respectively .See table 17 and 18

Table 17: Transition probabilities for Participation in Program

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.846	0.154	0.0
U	0.619	0.381	0.0
O	0.0	1.0	0.0
State/ period	July-December2016 to July-December 2017		
	E	U	O
E	0.818	0.182	0.0
U	0.643	0.357	0.0
O	0.0	0.5	0.5

Table 18: Transition probabilities for Non- Participation in Program

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.923	0.075	0.002
U	0.182	0.806	0.012
O	0.022	0.121	0.857
State/ period	July-December 2016 to July-December 2017		
	E	U	O
E	0.917	0.08	0.003
U	0.196	0.790	0.014
O	0.039	0.121	0.839

Empirical Analysis of Gabane's CBMS Data: Multinomial Logit Model

It is considered that the analysis of labour transitions in terms of flow frequencies that has been presented above is limited in the sense it does not permit robust determination of the individual factors on the chances of finding or losing a job. The analysis captured transitions between labour market states resulting from the joint influence of all the determining factors (such as age, gender, etc) acting together to impact on the individuals' decisions to, say, continue seeking employment or exiting the labour market (cf Bukowski and Lewandowski, 2005). In order to delineate the individual factors influencing people's transition decisions, a multiple regression model is required.

This study employs the multinomial logit (MNL) model to analyse the changes in labour market states in Botswana's labour market. This model is suitable for this task since it models the outcome variable, as categories that are not ordered; just as transitions across the labour market states (employment, unemployment and out-of-labour market) are not ordered. The working of the labour market, in response to factors determining labour market decisions, is such that by the end of the transition period[4], an employed person may continue to be employed, or may have moved to either the employment pool or the out-of-labour market (OLM) pool. Similarly, a person starting off in any of these pools may have moved to any of the other states by the end of the transition period.

MNL Model for Labour Market Transitions in January-June 2016 to January-June 2017 Period

Prior to the presentation of model parameter estimates, a description of the model variables and summary of key variables are important. Table 19 presents a description of variables, while Table 20 presentation summary statistics on key model variables.

Table 19: Description of Variables

Variable	**Variable Coding**	**Notation in Model**
Gender	Dummy variable 1 if male	gender (female=base category)
Age	Dummy variable 1 if in (15-24 years) 1 if in (25-34 years) 1 if in (35-39 years)	 ageyr1 (=base category) ageyr2 ageyr3
Education	1 (pre-school education) 2 (primary education) 3 (secondary education) 4 (higher education/training)	edu=1 (=base category) edu=2 edu=3 edu=4
Wages in cash (monthly)	Continuous	wagcshm
Participation in Labour Market Programme	Dummy variable 1 if participated	Lmktprog171 (no participation=base category)
Location of ward	Dummy variable 1 if in Gabane South East 1 if in Gabane South West 1 if in Gabane North West 1 if in Gabane North East	 local1 (=base category) local2 local3 local4

Source: Author analysis of data

[4] There are two transitions periods in the data used in this study. One period is from January-June 2016 to January-June 2017, while the other period is from July-December 2016 to July-December 2017.

Table 20: Summary Statistics on Key Model Variables for Gabane Youth

Variable	Frequency	Percent
Age		
15-24 years	1346	35.49
25-34 years	1717	45.27
35-39 years	730	19.25
Education		
Pre-school	29	0.77
Primary	101	2.67
Secondary	2843	75.05
Higher education/training	815	21.52
Gender		
Female	2161	56.97
Male	1632	43.03

The variables in Table 19, involving characteristics and variables relating to economic conditions were all used in an MNL regression model (with their short names as in the third column of the table). Table 21 presents the MNL regression estimates, indicating the individual factors that have influenced decisions on labour transitions between the three states between January 2016 and January 2017.

In Table 21, the dependent variable is labour market state, which represents the three labour market states of employment, unemployment and out-of-labour force (OLF). The normalisation of the model expresses the dependent variable as the probability of occurrence of employment state or OLF state relative to the probability of occurrence of unemployment state (referred as the base category).[5]

The results show that being male (compared to female) increases the multinomial log-odds for becoming employed relative to remaining unemployed by 0.446 units, ceteris paribus. The Z-statistic shows that this effect is highly statistically significant, even at the 1 percent level. On the other hand, although being male points to the likelihood of exiting the labour force, this is not statistically significant.

In terms of the age differential, being an older youth (relative to the base age of 15-24 years) increases the likelihood of getting employment than remaining unemployed. Consistent with this result, being an older youth reduces the likelihood of exiting the labour force, when unemployed, ceteris paribus.

[5] For details on the model description, see the literature review section.

Higher levels of education and training of youth[6], relative to the base of pre-school level of education is only indicative of promoting employment relative to the base of unemployment status, as these terms are not statistically significant. A broadly similar result holds when considering movement from the unemployment state to out-of-labour force.

The economic factor of remuneration (in cash) increases the log-odds of being employed than remaining unemployed by 0.0001 units, ceteris paribus. Consistently, higher remuneration reduces the probability of exiting the labour force by a similar magnitude. This finding seems to suggest that higher remunerations encourage youth to enter the labour market and obtain employment, rather remain unemployed. A possible corollary of this is that in response to low remuneration some may be discouraged from entering the labour market and obtaining jobs.

Another notable result is that participation in government labour market programmes significantly increases the probability of being employed relative to the probability of being unemployed. However, participation in labout market programmes is not statistically significant in transition from employment to OLF state.

Lastly, it turns out that there is location-effect on the transitions probabilities of youth across the labour market states in Gabane village. Results suggest that being in Gabane North East ward (compared to the referent ward of Gabane South East) increases the likelihood of employment relative to unemployment. It seems that as this happens, the likelihood of more youth joining the labour force, from the OLF status. But being in Gabane North West and South West compared to being in Gabane South East reduce the probability of exiting the labour force.

[6] The education variable is an indicator variable, which, for modelling purposes, has been defined, in terms of the number of years completed in school, as: 0-9 (preschool), 10-19 (primary education) and 20-29 (secondary education). The last category is that of higher education, which comprise the training component (represented by the variable reflecting the training, denoted by ntrain). In the model, these levels are coded as edu=1, edu=2, edu=3 and edu=4, respectively.

Table 21: Multinomial Model of Estimation of Transitions Probabilities in January-June 2016 to January-June 2017

Predictor Variables	**Transitions from Unemployment to:**			
	Employment		**Out-of-Labour Force**	
	Coefficient	*Z-value*	*Coefficient*	*Z-value*
Gender	0.446	(4.67)***	0.141	(1.18)
ageyr2	1.360	(12.10)***	-2.247	(-12.84)***
ageyr3	1.716	(12.16)***	(-3.765)	(-6.39)***
edu2	0.161	(0.30)	(-0.165)	(-0.18)
edu3	0.712	(1.51)	(-0.337)	(-0.39)
edu4	0.056	(0.12)	(0.038)	(0.04)
wagcshm	0.0001	(22.02)***	-0.0001	(-5.47)***
Lmktprog171	1.371	(3.17)***	-16.364	(-0.01)
local2	-0.020	(-0.16)	-0.683	(-4.66)***
local3	0.102	(0.82)	-0.701	(-4.07)***
local4	0.399	(2.62)**	0.791	(4.62)***
constant	-2.679	(-5.46)***	0.128	(0.15)
Number of obs = 3,788 LR Chi2(22) = 2761.10 Prob > Chi2 = 0.0000 Pseudo R2 = 0.3714	Log likelihood = -2.384.17			

Notes: *** means significant at 1 percent and ** means significant at 5 percent.

There is a possibility that women may face different experiences with respect to such factors as education, income, employment status, etc. In this context, it is expedient to estimate the MNL model separately for men and women. Table 22 presents results from estimating the equation for women.

Table 22: Multinomial Model of Estimation of Transition Probabilities for Women Transitions in January-June 2016 to January-June 2017

Predictor Variables	Transitions from Unemployment to:			
	Employment		Out-of-Labour Force	
	Coefficient	*Z-value*	*Coefficient*	*Z-value*
ageyr2	1.189	(7.74)***	-2.286	(-10.49)***
ageyr3	1.426	(7.48)***	-4.350	(-4.31)***
edu2	0.219	(0.27)	14.832	(0.01)
edu3	0.681	(0.971)	14.776	(0.01)
edu4	-0.153	(-0.21)	15.172	(0.01)
wagcshm	0.0001	(17.85)***	-0.0002	(-4.09)***
Lmktprog171	1.312	(2.45)**	-15.292	(-0.01)
local2	-0.080	(-0.48)	-0.732	(-3.88)***
local3	0.034	(0.20)	-0.854	(-3.57)***
local4	0.474	(2.28)**	0.829	(3.57)***
constant	-2.592	(-3.60)***	-14.904	(-0.01)
Number of obs = 2159 LR Chi2(22) = 1655.27 Prob > Chi2 = 0.0000 Pseudo R2 = 0.3861		Log likelihood = -1315.89		

Notes: *** means significant at 1 percent and ** means significant at 5 percent.

The results in Table 22 seems quite similar to those obtained when the MNL model was estimated for both men and women together. The only difference lies in the location-effect. The results suggest that the extent to which female youth of Gabane face different experiences with respect to such factors as education, income, employment status, is not statistically significantly different from their male counterparts.

The results obtained from estimating the model for men are presented in Table 23.

Table 23: Multinomial Model of Estimation of Transition Probabilities for Men in January-June 2016 to January-June 2017

Predictor Variables	Transitions from Unemployment to:			
	Employment		**Out-of-Labour Force**	
	Coefficient	*Z-value*	*Coefficient*	*Z-value*
ageyr2	1.539	(9.33)***	-2.160	(-7.27)***
ageyr3	1.990	(9.10)***	-3.193	(-4.32)***
edu2	0.053	(0.07)	-0.583	(-0.53)
edu3	0.758	(1.19)	-0.878	(-0.87)
edu4	0.216	(0.33)	-0.549	(-0.54)
wagcshm	0.0001	(13.17)***	-0.0001	(-3.71)***
Lmktprog171	1.476	(1.92)*	-13.314	(-0.002()
local2	0.088	(0.50)	-0.593	(-2.54)
local3	2.47	(1.24)	-0.431	(-1.56)
local4	0.347	(1.52)	0.794	(3.10)***
constant	-2.327	(-3.52)****	0.687	(0.68)
Number of obs = 1629 LR Chi2(22) = 1099.57 Prob > Chi2 = 0.0000 Pseudo R2 = 0.3562		Log likelihood = -993.75		

Notes: *** means significant at 1 percent and ** means significant at 5 percent.

As with the results in Table 22, the results obtained from estimating the MNL model for men are similar to those obtained using both men and women together. These findings seem to corroborate the argument that the extent to which female youth of Gabane face different experiences with respect to such factors as education, income, employment status, is not statistically significantly different from their male counterparts.

In making comparison with results in analysis of transition probabilities, it can be observed that there is consistency in the empirical results. In particular, the older youth, compared to the younger ones, as well as the males, compared to females, have higher chances of employment (or remaining employed). Consistency also prevails with respect to the programme participation variable. In the case of participation in the government programmes, the discernible positive effect of programme participation on transition probabilities seems to be reflected in the statistically significant effect, with the correct sign for the coefficient, of programme participation in the model.

The multinomial relative log-odds for moving from employment to the out-of-labour market state have similar signs and significance, as is the case for the relative log-odds of moving from employment to unemployment for age and the individual's income. The difference lies in the relative log-odds for exiting the labour force as individuals' education level increases, and due to participation in government programmes which, although have the correct signs, are statistically insignificant at the 5 percent level. Similarly, the training variable still has the positive coefficient, suggesting that a one unit increase in training increases the relative log-odds of exiting the labour market compared to being employed.

In generalising the results, it can be stated that more men (compared to women) tend to remain in employment and less likely to lose their jobs or exit the labour market; and older youth tend to be employed and less likely to lose their jobs or exit the labour market. Similarly, people with higher incomes tend to remain in employment and less likely to lose their jobs or exit the labour market. However, the young people with more training tend to become unemployed and/or exit the labour market.

MNL Model for Labour Market Transitions in July-December 2016 to July-December 2017 Period

The forgoing empirical analysis of transitions between labour market states between January-June 2016 and January-June 2017, using the MNL model is replicated for the transitions between July-December 2016 to July-December 2017 period.

Table 24 presents the MNL regression estimates, indicating the individual factors that have influenced decisions on labour transitions between the three states across the second period of analysis of July-December 2016 to July-December 2017.

Table 24: Multinomial Model of Transition Probabilities in July-December 2016 to July-December 2017

Predictor Variables	**Transitions from Unemployment to:**			
	Employment		**Out-of-Labour Force**	
	Coefficient	*Z-value*	*Coefficient*	*Z-value*
Gender	0.517	(5.33)***	0.100	(0.83)
ageyr2	1.273	(11.28)***	-2.228	(-12.60)**
ageyr3	1.606	(11.29)***	-3.728	(-6.32)***
edu2	-0.032	(-0.06)	-0.298	(-0.32)
edu3	0.497	(1.05)	-0.388	(-0.45)
edu4	-0.109	(-0.23)	-0.089	(-0.10)
wagcshm	0.0001	(22.49)***	-0.0001	(-5.51)***
Lmktprog172	1.298	(3.29)***	-1.233	(-1.15)
local2	-0.006	(-0.05)	-0.654	(-4.43)***
local3	0.29	(0.23)	-0.780	(-4.45)***
local4	0.416	(2.68)**	0.777	(4.48)***
constant	-2.450	(-4.99)***	0.201	(0.23)
Number of obs = 3,788 LR Chi2(22) = 2831.36 Prob > Chi2 = 0.0000 Pseudo R2 = 0.3832		Log likelihood = -2278.34		

Notes: *** means significant at 1 percent and ** means significant at 5 percent.

The results associated with the two MNL equations for the outcomes of employment and out-of-labour force, obtained in Table 24, are quite similar to those obtained in Table 21. Thus, the interpretation provided above applies to the results in Table 24 also.

Predicted Probabilities

As is commonly argued, given the multiple equations entailed, as well as the interpretation in terms of relative probabilities, the results from the MNL logit model are generally difficult to interpret and/or understand (see Stata.com, mlogit postestimation). One of the ways to enhance understanding the model results is to use the marginal effects of the model's predictors. Another way is to compute predicted probabilities of observing each outcome category. This paper presents the latter, given the advantage of being able to graph the predicted probabilities for each outcome, against the predictor under consideration. (For brevity, only the predicted probabilities associated with two predictors, gender and participation in labour market programme, are presented.)

Figure 1 presents predicted probabilities of observing all the three outcomes of categorical dependent variable, against participation in labour market programme. The graph shows changes in predicted probabilities as participation in labour market programmes goes from zero to unity (from nonparticipation to participation). As can be seen in the graph for employment status (Employ), with participation in the programmes, the predicted probability of employment rises – this is consistent with the results reported above. Similarly, the graph for unemployment status (Unemploy) shows that the youth participating in government programmes face lower predicted probabilities for unemployment.

Figure 1: Predicted Transition Probabilities in January-June 2016 to January-June 2017 by Labour Market Participation

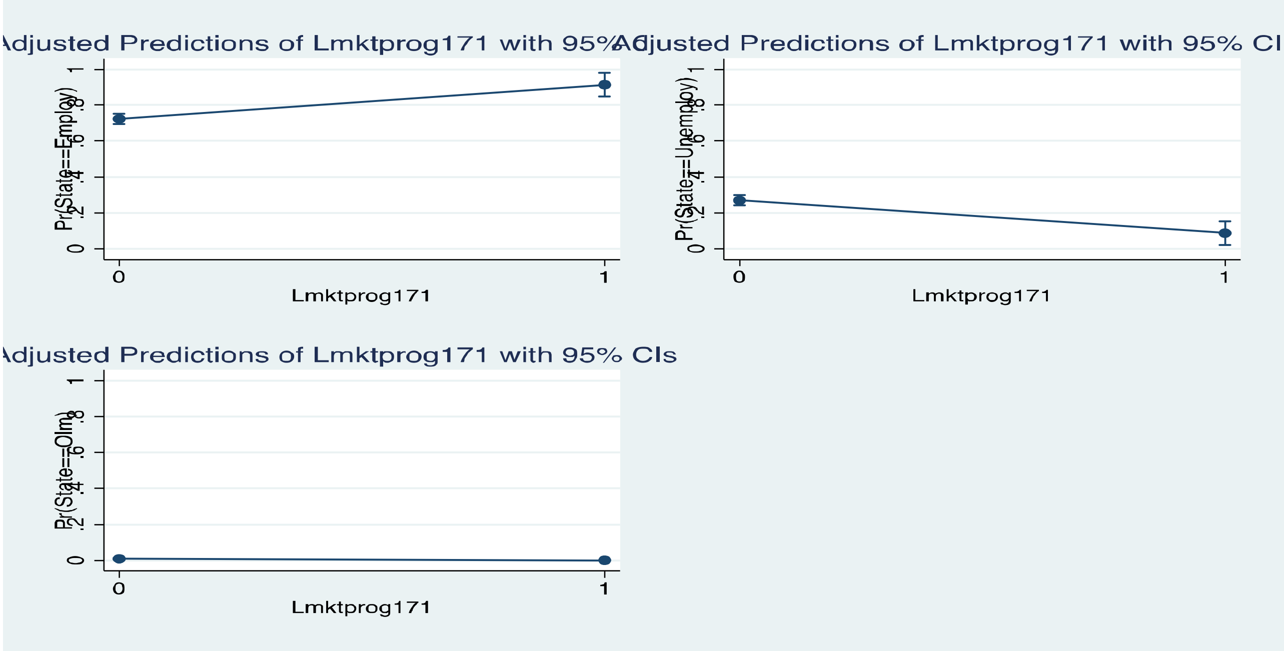
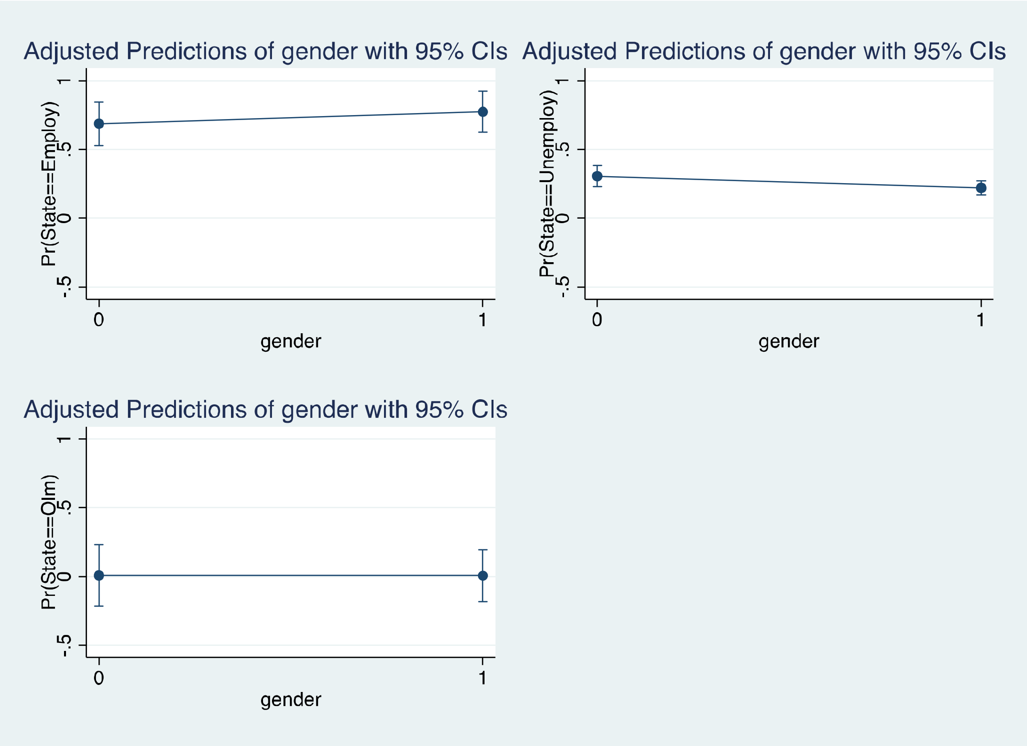


Figure 2 presents predicted probabilities associated with the gender indicator variable. The graph for the employment status (Employ) shows that the older the respondent is, the greater the predicted probability of employment. Meanwhile, the graph for the unemployment status (Unemploy) shows that the older youth face lower predicted probabilities for unemployment; implying that older youth face less unemployment problem than the younger youth. However, the graph for the out-of-labour force status (olm) suggests that predicted probabilities do not change for this status across the age groups.

Figure 2: Predicted Transition Probabilities in January-June 2016 to January-June 2017 By Gender



Conclusion

This study intended to determine the factors (relating to individual characteristics and other economic variables) that influence the movements of the Gabane youth across the labour market positions of employment, unemployment and out-of-labour market. The study used the Markov chain analysis of the labour market transition probabilities of the youth, followed by multiple regression analysis, using the multinomial logit (MNL) model.

The analysis in terms of transition probabilities indicates that males, compared to females, have higher probabilities of remaining employed or moving from unemployment state to employment. However, disaggregating the analysis by estimating the model for males and females separately does not produce different results. This seems to indicate that the differences in males versus females is not statistically significant.

In terms of age, the transition probabilities suggest that, in general, older youth have higher probabilities of remaining in the employment state, or moving from unemployment to employment, compared to the younger youth. It is encouraging that the findings in the context of the MNL model are consistent with those in the transition probabilities. In addition, the MNL model results indicate that the youths with higher cash wages and who participated in the government labour market programmes faced higher probabilities of remaining in employment, or movement from unemployment state to employment, as compared to those with lower wages or did not participate in the government programmes. The positive impact relating to participation in government programmes is noteworthy, given the fact that the survey data indicates the majority of the Gabane youth (3767 of the total of 3802, which is about 99.26%) did not participate in them in 2017. Only 28 youth (about 0.74%) were participating in the five government programmes (including Youth Development Fund (YDF), National Service Programme (NSP), Young Famers Fund (YFF), National Internship Programme (NIP), and Government Voluntary Scheme (GVS)).

The regression model results also suggest that education has no effect on the transition from unemployment to employment – that is, the education variable is not statistically significantly different from zero. This suggests need for improvements to the education system so as to provide education and training that meet the needs of industry.

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