working paper
CBMS-2020-10

Determinants of Unemployment and Labour-Market Transitions for Youth in Botswana

Happy Siphambe
Malebogo Bakwena
Lexi Setlhare
Mavis Kolobe
Itumeleng Oageng
Keamogetse Setlhare
Tshegofatso Motswagae

May 2020

pep
partnership for economic policy

PAGE
policy analysis on growth and employment

Determinants of Unemployment and Labour-Market Transitions for Youth in Botswana

Abstract

Africa has a youthful population and Botswana is no exception. As a result, Botswana suffers from high youth unemployment problems. Hence, this paper seeks to empirically investigate how the socio-economic characteristics of the youth of Gabane village in Botswana influence their transitions among the three labour market positions, being state of employed, unemployed and seeking for work, and being out of the labour market between 2016 and 2017 for similar periods. The extent of transitions is measured in terms of the Markov transition probabilities of the youth, followed by multiple regression analysis using the multinomial logit model. The data was collected using Community-Based Monitoring System (CBMS) from all households in Gabane Village. This dataset provides a great opportunity that allows investigation of the factors influencing the transitions of people in the cross section of the population and provide significant policy proposal for consideration. Findings from the study indicate that the individual characteristics of the Gabane youth play a role in determining their transition probabilities across the labour market outcomes. Notably, being male versus being a female increases the relative probability of being employed or moving from the unemployment to employment state; the relative probability of moving from unemployment to employment increases with the age of the youth. The results also indicate that, despite the low-level of participation of youth in government programmes, that, participation in government programmes versus nonparticipation reduces the likelihood of being unemployed and education had no effect on the transition from unemployment to employment – that it is not statistically significantly different from zero. The study resulted in the following policy recommendations : There is need to reduce or eliminate obstacles that prevent the youth from participating in government programmes in large numbers and to provide education and training that meet the needs of industry. Policymakers need to require training institutions to involve industry so as to design education and training programmes that will provide the youth with the skills needed in the labour market.

Authors

Prof Happy Siphambe
Team Leader (PEP project),
University of Botswana
Gaborone, Botswana
Siphambe@mopipi.ub.bw

Dr Malebogo Bakwena
Deputy Team Leader (PEP project), University of Botswana
Gaborone, Botswana
thokweng@mopipi.ub.bw

Dr Lexi Setlhare
Team member (PEP project),
University of Botswana
Gaborone, Botswana
setlharelexi@gmail.com

Ms Mavis Kolobe
Team member (PEP project),
University of Botswana
Gaborone, Botswana
Mavis.moalosi@mopipi.ub.bw

Ms Itumeleng Oageng
Team member (PEP project),
University of Botswana
Gaborone, Botswana
Itumeleng.oageng@mopipi.ub.bw

Dr Keamogetse Setlhare
Team member (PEP project),
University of Botswana
Gaborone, Botswana
SETLHARK@mopipi.ub.bw

Ms Tshegofatso Motswagae
Team member (PEP project),
BA ISAGO University
Gaborone, Botswana
motswagaetl1986@gmail.com

Acknowledgements

This research work was carried out with financial and scientific support from the Partnership for Economic Policy (PEP) (www.pep-net.org) with funding from the Department for International Development (DFID) of the United Kingdom (or UK Aid), and the Government of Canada through the International Development Research Center (IDRC).
The authors are also grateful to Bernadette Mandap, Marie Celeste Diouf and Steffie Calubayan for technical support and guidance, as well as to the Department of Surveys and Mapping director for assistance with generating and validating the poverty maps for Gabane village. We extend our gratitude to the leadership of Gabane village (Kgosi and dikgosana), the Village Development Committee, Councillors and the Gabane residents for their support during data collection and Kgotla meetings. University of Botswana Finance Department provided valuable support in terms of management of the grant to which we are grateful. Last but not least, the authors would like to thank Prof Alellie Sobrevinas, Dr. Felix Ankomah Asante, Dr. Nanak Kakwani, Dr Nancy Spence and Dr Sudarno Sumarto among others for valuable comments and suggestions.

Contents

List of tables

List of abbreviations

CBMS Community-Based Monitoring System

DFID Department for International Development

IDRC International Development Research Center

MNL Multinomial Logit

PEP Partnership for Economic Policy

SDG Sustainable Development Goals

UB University of Botswana

VDC Village Development Committee

Executive summary

Economic theory explains how the aggregates of employment and unemployment are determined by the business cycle of the economy. During the expansionary phase, every member of the labour force can find a job with relative ease, meaning that every unemployed member of the labour force faces a higher probability of being employed. At the same time, for those with jobs, the probability of losing their jobs decreases (Kucharski & Kwiatkowski, 2006). The converse is true in the contractionary phase of the business cycle.

However, the aggregate unemployment rate may also be influenced by worker flows between labour-market states: employment, unemployment, and out-of-the-labour market. Worker flows refer to transitions of members of the labour force from one labour-market state to another. Thus, it is important to analyse worker flows (or labour-market transitions) among these labour-market states for two main reasons. The first is that, while aggregate unemployment may result from a lack of job expansion in the economy, some unemployment arises as a consequence of job mobility (i.e., transitions of workers from job to job; see Bosler & Petrosky-Nadeau, 2016). In this regard, the larger the magnitude of the transitions, the greater is the influence on the aggregates of employment and unemployment. For example, large flows from employment to unemployment decrease employment on one hand and increase 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) results in a decrease in unemployment. Lastly, large flows from out-of-the labour market to either unemployment or employment 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 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 socioeconomic characteristics of individuals (gender, level of education, type of skill, and age) play an important role. These individual characteristics influence the flows of people into various labour-market positions, which can be measured by probabilities of losing jobs or finding new ones. We sought to undertake an empirical investigation of how the socioeconomic characteristics of youth in Gabane village (as well as labour-market conditions such as wages and government labour-market programmes) influence transitions among the three labour-market positions.

We measured transitions in terms of Markov transition probabilities and a multinomial logit model. The Markov analysis method investigates the movements/flows of people into and out of the labour-market states between two time periods (t, the current period, and t-1, the previous period). This method works under the assumption that only one movement is possible between t and t-1 and that all employees in a given state have the same probability of moving from one state to another (Mahoney & Milkovich, 1971).

Empirical analysis of labour-market transitions among youth in Gabane Village was enabled by the data generated from the implementation of the Community-Based Monitoring Study Project (hereafter, CBMS) supported by the Partnership for Economic Policy through the CBMS Network Office. The pilot implementation of the CBMS in Botswana, particularly in the study site of Gabane Village in Kweneng District, generated household and individual data on multidimensional poverty and indicators for monitoring sustainable development goals (SDGs) and provided detailed microdata that enabled the analysis of worker flows among the labour-market positions from the perspective of workers, not of employers (see Siphambe et al., in press). It should be noted that the CBMS data are census not sample data—every person in the village had to be interviewed, except for those that refused or were not available (even after repeated visits by research assistants).

Data were collected using structured questionnaires that included the Household Poverty Questionnaire and the Community Poverty Questionnaire. The CBMS-Accelerated Poverty Profiling (CBMS APP)[1] data-collection software was installed on the tablets used for the census at the project sites. Tablets were used for pre-testing the questionnaires and for the whole data collection process. An addendum to the survey questionnaire that captured additional questions related to the study of youth unemployment was embedded into the core household questionnaire and was administered at the same time.

Research assistants had access only to the questionnaire in the tablet while field supervisors had access to completed questionnaires and were able to check for consistency and validate them. A completed questionnaire was only sent to the server after it was checked by field supervisors, corrected by the research assistants, and validated by the supervisors. The analysis of the survey data used STATA software.

Data collection took place between February and April 2018 and covered all households in Gabane. On average, fifty-two households were covered per day, and the duration of the interview depended on the number of people in a household. The longest interview took about three hours.

Thematic research questions were introduced into the standard CBMS questionnaire to capture the labour-market states of individuals for two periods (from January-June 2016 to

[1] Developed by the CBMS Network Office based at De La Salle University, Manila, the Philippines.

January-June 2017 and from July-December 2016 to July-December 2017). Hence, this study used cross-sectional data. During data collection, enumerators entered GPS coordinates to capture the location of the household whose members were interviewed. The dataset provides a great opportunity to investigate the magnitude of the transitions in the cross section of the community. Notably, the microdata made examination of gross transitions possible (transitions of persons, regardless of their individual characteristics) as well as transitions determined by individuals' socioeconomic characteristics.

Key Findings of the Study

1. Men, compared to women, had higher probabilities of remaining employed or moving from unemployment state to employment.
2. Older youth had higher probabilities of remaining in the employment state or of moving from unemployment to employment, compared to younger youth.
3. The majority of Gabane youth (99%) did not participate in any government employment programme in 2017.Youth who participated in government labour-market programmes faced higher probabilities of remaining in employment or of moving from the unemployment state to employment, as compared to those with lower wages or who did not participate in government programmes.

Policy Implications of the Study

1. Women have fewer job opportunities as a result of limited jobs, occupational segregation, and (perhaps) skills mismatch from training and education.
2. There is need to provide more experience for youth during and after education and training.
3. Government employment programmes are not accessible to youth because of lack of knowledge and/or complexities in the processes of access. Also, the youth who participated in government programmes have more chances of moving from the unemployment and out-of-the-labour-force states to employment or to self-employment.

1 Introduction

1.1 Context of the study

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% a year, an achievement that puts Botswana on par with Asian "tigers" such as Thailand and Korea.

For the most part, the high growth rate has been facilitated by carefully invested mineral wealth 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 a decline in some industries as a result of the diamond boom. However, a major challenge that mars Botswana's success story is the coexistence of a weakly diversified economy. As result, the country had a small production base characterised by small productive employment opportunities. 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 high levels of unemployment.

Botswana's youth population (considered to be those between 15 and 39 although, generally, the category of "youth" is internationally defined as 15-24[2]) tends to experience higher unemployment rates than the older population because 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 women's unemployment higher than men's (26.9% and 23.6%, respectively; Statistics Botswana, 2016). To some extent, the high unemployment rate for this particular group is a result of high-school-dropout rates in the country. Between 2012 and 2014, 8,051 students (of which 5,031 were young women) left secondary school.

In Botswana, many studies have been carried out on youth unemployment and on unemployment in general, but they have not examined people's gross transitions or the transitions determined by individuals' socioeconomic characteristics.

Ama (2008) studied the transition from higher education to employment among graduates of Faculty of Social Sciences at the University of Botswana. The study, among other things, was interested in graduates' average waiting time before they secured their first employment and the extent to which their jobs were appropriate to their levels of education. Even though the study was concerned transitioning from one labour-market

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

state to the other, there was no attempt to determine the socioeconomic characteristics of the graduates that influenced their transitions, and we have sought to contribute to filling this gap.

Kemiso and Kolawole (2017) assessed the factors that contributed to unemployment among rural youth among youth in the Okavango Delta, Botswana. Specifically, they analyzed socioeconomic and institutional factors (age, education, training, etc.) that influenced unemployment among rural youth in their study area, but did not examine how those factors affected transitions from one labour-market position to another. Last, Nthomang and Diraditsile (2015) also studied youth unemployment in Botswana, focusing on identifying the strengths and challenges of the past government efforts to address youth unemployment in order to develop more effective and relevant interventions.

Therefore, this paper seeks to examine gross transitions (transitions of persons, regardless of their individual characteristics) as well as transitions determined by individuals' socioeconomic characteristics of the youth in Gabane across the three labour market positions of employment, unemployment and out-of-the-labour market.

1.2 Research questions andobjectives

Research Objectives

The main objective of the study is to empirically investigate the socio-economic characteristics (age, education, gender, programmes, cash wages) of the youth of Gabane village in Botswana influence their transitions among the three labour market states. This broad objective is explored through the following sub-objectives:

- To investigate whether individual characteristics (age, education, gender) influence transition probabilities.
- To investigate whether economic conditions (cash wages, government programmes) influence transition probabilities.
- To provide evidence-based policy advice.

Research Questions

- Do the following individual characteristics (age, education, gender) influence transition probabilities?
- Do the following economic conditions (cash wages, government programmes) influence transition probabilities?
- What evidence-based policy can be recommended?

To answer the reseach questions, we first modelled individual experiences using the Markov transition probabilities, and then used a multinomial logit model to quantify the probability of transitioning from one labour market state to another.

2 Literature review

The literature review provided useful information regarding importance of analyzing transitions across the labour-market states and the appropriateness the Markov chain process and the Multinomial logit model. Some past studies have employed the same methods of analysis as ours and we have presented their main findings for comparative analysis.

Theoretical Literature Review

Although aggregate unemployment rates may be the result of structural problems in the economy (e.g., inadequate creation of job opportunities), it can also be influenced by worker flows between labour-market states, which means that such transitions 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 geared to improving how information on labour-market conditions is provided to the unemployed in order to expedite their chances of getting new jobs. In cases in which 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., from January-June 2016 to January-June 2017 and from July-December 2016 to July-December 2017), policies are needed that are more of a structural type, including suitable training and job-creation and income-support schemes (see Arif, Khan Kiani & Sheik, no date).

Studies conducted on individual labor market dynamics have utilized duration models, binary logit/probit models, and/or multinomial logit models, and still others have modelled transitions among some labor force states as a Markov chain process. The 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.

Researchers who have used a multinomial logit (hereafter, MNL) model have considered such a model to be suitable in the context of a qualitative dependent variable (that is, when the dependent variable comprised more than two unordered categories, as was the case with the three labour-market positions of employment, unemployment, and out-of-the-labour market; see, e.g., Bukowski & Lewandowski, 2005; and Kucharski & Kwiatkowski, 2006). The MNL model can be used to estimate the risk that a particular labour-market position/state will be achieved (see Kucharski & Kwiatkowski, 2006; and Fabrizi & Mussida, 2009). In addition, estimating the multinomial function means that the probability that a certain event will occur can be quantified, as determined by individual worker characteristics (e.g., age, education, etc.) and other factors. The use of a multiple regression model to analyse the effect of covariates on probabilities is crucial to eliminate the potential for misleading results that might arise from a third-variable effect. For example, the transition probabilities associated with the individuals' ages may mainly be the result of the effect of a variable other than age.

Another strand of the literature has assessed labour-market mobility by developing matrices to capture the movement of persons across labour-market states (see, for example, Foley, 1997; Fabrizi & Mussida, 2009, and Arif, Khan Kiani & Sheik, no date). Transitions across labour-market states indicate the extent of workers'/persons' mobility in the labour market. The greater the probability of transitioning from one labour-market state to another, as opposed to the probability of remaining in the same state, the higher the mobility of workers. The greater the probability 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.

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

$$P_r(X_t = i|X_{t-1}, \dots, X_1) = P_r(X_t = i|X_{t-1})$$

where the index $i = 1, \dots k$, stands for labour-market state.

In this context, the probability of transitioning from state i to state j between time period $t - 1$ and period t depended only upon the immediate past value, implying that the process had no long memory (for details, see Fabrizi & Mussida, 2009). Given the three labour-market positions assumed in this study, nine probabilities could be calculated. These probabilities give the probability transition matrix, $M_{(t)} = \left[P_{ij(t)}\right]$. Often the literature has axiomatically assumed that transition probabilities were 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.[3]

Empirical Literature Review

Several studies have empirically examined the transition probabilities of workers across labour-market positions in various countries.

The objective of Van der Merwe's (2016) empirical study was to understand how individual characteristics and circumstances affected the probability of being in a particular labour-market state in the next year. She considered four mutually exclusive labour-market states: employed, unemployed, marginally attached to the labour force, and out-of-the-labour-force. She examined individual changes in labour-market status from year to year, using one-year-ahead transition probabilities. She found that more than 40% 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% remained employed in the next year. The results for transitions into the other three labour-market states also showed that an individual's labour-market status was unlikely to change from one year to the next. To unravel the relative importance of individual characteristics associated with future labour-market status, she used a multinomial logit framework. The results revealed that being a woman increased the probability of being outside the labour force in the following year by around 1.4 percentage points. This was possibly due to earlier retirement or family responsibilities. Van der Merwe also established that having a degree or diploma (compared to finishing high school alone) increased the probability of being employed in the following year by around 1 percentage point and lowered the probability of being unemployed in the following year by around half a percentage point. In contrast, incomplete schooling (compared with high school graduation) reduced the probability of becoming employed by almost 3 percentage points and increased 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. Van der Merwe noted 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.

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

Kavuma, Morrissey, and Upward (2015) examined the flow of workers among employment states, the role of education in these transitions, and the impact of transitions on earnings. They used panel data for three waves (2005-2006, 2009-2010, and 2010-2011) of household surveys in Uganda. Using a Markov chain process, they estimated transition-probability matrices and found bidirectional transitions between formal and informal employment, though workers had a higher tendency to transition from formal to informal states as opposed to the opposite direction. Using probit models to investigate the relationship between education and transitions, found that the informal-to-formal transition increased with education but that formal-to-informal movement, or from not working to employment declined with education.

To quantify the magnitude of transitions across occupational categories, Cuesta and Bohorquez (2014) used a panel of households that were representative of Colombia's main metropolitan areas during the 2008-2009 period. Their results showed that transitions among occupations were large and asymmetric: they were disproportionally more likely to take place from formal to informal occupations than vice versa. They reported that such transitions also differed for salaried workers compared with the self-employed and according to workers' poverty status. Salaried workers were more likely to transition into other salaried jobs, while the self-employed were more likely to transition into unemployment or out of the labor force.

Fabrizi & Mussida (2009) investigated the determinants of labour-market transitions in Italy. They applied a Markov chain approach and a multinomial logit model to individual-level data from the 1993-2003 Italian labour force surveys and examined labour-market transitions among the states of employment, unemployment, and inactivity. Their results showed that the probability of leaving the labour force was reduced for men. In other words, women were more likely to leave the labour force, signaling either a discouragement effect for women or the fact that women had more family responsibilities compared to men. They also established that having a university degree increased the likelihood of leaving unemployment as compared to those with solely a high-school diploma or who attended only compulsory education, but a degree did not seem to affect the likelihood of exiting the labour force. They noted that aging reduced the likelihood of leaving the labour force, perhaps because greater age implied greater responsibilities and, thus, a smaller likelihood of exiting the labour market. Finally, they also found that being married accelerated the probability of leaving the labour force, that work experience accelerated the exit from unemployment, and that family size did not affect transitions from one labour-market state to another.

Audus, Berde, and Dolton (2005) empirically examined labour-market transitions in Hungary. They sought to determine the factors that predicted whether individuals would be unemployed within a month as opposed to working, studying, or serving in the military. To do this, they estimated a probit model based on initial labour-market outcome (1 if unemployed; 0 otherwise) and found that women tended to be considerably more likely to be unemployed compared to men. They also found that school type and education performance were both significant predictors of being unemployed. Individuals who did well on their matriculation examinations tended to be much less likely to be unemployed, reflecting the fact that they were more inclined to remain in education (that is, in the out-of-labour force), while those who did poorly looked for work and often ended 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 choosing to seek employment instead, making them much more disposed to an initial spell of unemployment.

Taşçı and Tansel (2005), using 2000 and 2001 Household Labour Force Survey panel data from Turkey, computed Markov transition probabilities by gender, marital status, and rural-urban residence for three labour-market states: employment, unemployment, and not in labour force. Moreover, they carried out multinomial logit regressions. Their major findings include these: while the probability of moving from unemployment to employment was lower for urban women than for urban men, the probability of moving from employment to unemployment was higher, leading to a higher unemployment rate for women. The probability of losing a job decreased with education.

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

Steiner and Kwiatkowski (1995) presented an empirical analysis of labour-force dynamics in Poland between May 1992 and February 1993 after the country 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 microdata from the quarterly) Polish Labour Force Survey (92/II, 92/III, 92/IV, 93I. These transitions were related through a dynamic microeconomic Markov Model of individual labour force transitions to various demographic and socioeconomic characteristics of the labour force, labour-market indicators, and other structural variables. The sets of explanatory variables taken into account in estimating transition models included individual and household characteristics (age, disability, education, marital status and, for women, children by age group); labour market indicators (type of region, urban agglomeration, and regional unemployment rate); and time dummies that accounted for changes in general labour-market conditions associated with the economic transition as well as for seasonal effects and other variables (Steiner & Kwiatkowski, 1995). Quarterly empirical transition rates between labour-force states (in percent) from May 1992 to February 1993 all declined between 92I and 93I, with the exception of the transition rate from employment to unemployment. The transition rate from employment into non-participation was much higher than into unemployment in the first two periods but dropped below the level of the latter in the last period. This seemed to reflect the widespread use of early-retirement schemes as a means of labour-force adjustment rather than seasonal factors alone. 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 was mainly due to the drop in the transition rate into employment in the last quarter. The transition rate from non-participation into employment or unemployment and, hence, the outflow rate from non-participation, declined substantially over the observation period (Steiner & Kwiatkowski, 1995).

Foley (1997) used information from a nationally representative longitudinal survey of Russian citizens to analyze 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 was identified. The results indicated that the probability of losing a job increased by 75% from 1992 to 1996 while the re-employment probability declined by 24%, leading to an increase in long-term unemployment. Foley also found that education was a factor in exiting unemployment to a job: by 1995-1996, 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 carried the greatest weight, increasing re-employment probability by 27.5 percentage points.

Synthesis of the empirical literature review (A critical review)

In explaining unemployment and transitions in various labour markets, most studies have computed transition probabilities among the labour-market states of employment, unemployment, and out-of-the-labour-force under Markovian assumptions and have then presented multinomial logit models to analyse the determinants of labour-market states (Cilasun, Acar and Gunalp, 2015; Van der Merwe, 2016; Taşçı & Tansel, 2005; and Fabrizi & Mussida, 2009). Most studies have determined transition probabilities by gender, age, education, occupation, and marital status (Cilasun, Acar and Gunalp, 2015) and Taşçı & Tansel, 2005, e.g.). However, Kavuma, Morrissey, and Upward (2015) estimated conditional transitional probabilities using the Markov chain process and probit models and included three transitions: not working to working (either formal or informal), formal to informal employment, and informal to formal employment. Audus, Berde, and Dolton (2005), in contrast, examined the nature of the school-to-work transition in economies shifting into a market economy.

In examining and comparing labour market dynamics, most studies have used panel data (Kavuma, Morrissey & Upward, 2015; Taşçı & Tansel, 2005; and Bosch & Maloney, 2007, e.g.) because the panel feature allows the measurement of changes between successive quarters and years and also because panel surveys provide detailed information regarding subjects' employment status, social security coverage, demographic characteristics, working hours, labour and income, living conditions, job characteristics, and socioeconomic conditions (Cilasun, Acar & Gunalp, 2015). Other studies have used longitudinal data (Fabrizi & Mussida, 2009; Audus, Berde & Dolton, 2005; Van der Merwe, 2016, e.g.) because such data include information from individuals and households regarding economic and subjective well-being, and labour-market and family dynamics, allowing for estimation of labour-market flows and valuable analyses of labour mobility.

The choice of the time span or period of research on mobility analysis has been based on a variety of factors. Cilasun, Acar and Gunalp (2015) and Taşçı and Tansel (2005), for example, conducted their studies following economic and financial crises that had major repercussions for labour markets, analyzing worker transitions across different market states to determine whether labour-market-policy reforms alleviated the adverse effects of the crisis. Audus, Berde and Dolton (2005) noted a major policy concern in transitional economies that were accompanied by rapidly rising levels of unemployment because of the introduction of market systems. Fabrizi and Mussida (2009), analyzed flows between labour-market states and their determinants. Specifically, they analyzed whether labour-market intervention and regulations introduced in the 1990s acted in the expected direction—that is, helped disadvantaged groups such as women and young people.

Most studies on labour-market transitions have covered a wide age group between 14-15 and 64-65 and have not focused specifically on youth (Cilasun, Acar & Gunalp, 2015; Fabrizi & Mussida, 2009; Kavuma, Morrissey & Upward, 2015; Taşçı & Tansel, 2005). Few studies have recognized that young people acquire more education and stay in full-time education longer, especially in European countries. As a result the length of the school-to-work transition is has increased (Audus, Berde & Dolton, 2005; e.g.); their research, therefore, focused on the younger population.

Variables such as age, gender, and education have had the same sign—that is, the way in which these variables affected labour-market transitions was the same regardless of whether the setting was a developing or a developed country. Some variables, such as family networks, health status, work experience, family size, and migrant status, among others, affected labour-market status transitions but these variables have not been widely used in the literature. Where they have been used, they have carried different signs depending on labour-market conditions in the country in which the study was conducted.

Studies on unemployment and labour-market transitions in Africa and on youth in that context, which is the group most affected by unemployment, are very few. Interestingly, most of the empirical literature on this topic did not include government labour-market programmes in their analyses as we did.

3 Methodology and data

We first modelled individual experiences using Markov transition probabilities and then, because of the limitations of this approach (transition probabilities could only be observed in the context of bivariate relationships), we then used a multinomial logit model to quantify the probability of transition from one labour-market state to another, which allowed for the confluence of multiple variables.

The data we analysed were collected via a CBMS survey of the labour-market states of youth (aged 15-39) in Gabane, Botswana, a location chosen on the basis of high unemployment (17.4%) in the village during the 2011 Population and Housing Census and also because of its proximity to Gaborone, where the research team was based. During the census period, the village showed one of area's highest unemployment rates.

To obtain the microdata 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 vs. January-June 2017 and July-December 2017. In each period, the questionnaire sought information from youth aged 15-39 years regarding on their employment status, whether they had participated in government intervention programmes, and the specific types of government programmes they had participated in.

Meanwhile, information on respondents' individual characteristics (age, gender, educational qualification, etc.) was obtained using the standard CBMS survey instrument.
The first part of the methodology of this study employed the Markov chain model to investigate transition probabilities. At the aggregate level, labour-market-transition probabilities can be summarized in the matrix presented in the following table.

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

		Destination		
$\boldsymbol{i,j}$	Origin state	Employed	Unemployed	OLF
	Employed	$P(E_t\|E_{t-1})$	$P(U_t\|E_{t-1})$	$P(O_t\|E_{t-1})$
	Unemployed	$P(E_t\|U_{t-1})$	$P(U_t\|U_{t-1})$	$P(O_t\|U_{t-1})$
	OLF	$P(E_t\|O_{t-1})$	$P(U_t\|O_{t-1})$	$P(O_t\|O_{t-1})$

Notes: 1–OLF denotes out-of-the-labour-force. 2–The labour-market states were $i, j = \{E, U, O\}$. 3–E =employed, U =unemployed, and O =OLF.

Table 1 indicates the probability of transitioning to a particular labour-market state in the current period (t), conditional on the individual's having been in a specific state in the previous period $(t-1)$. For example, $P(U_t|E_{t-1})$ refers to the probability that an individual was unemployed at time t, conditional on being employed at time $t-1$.[4]

The second part of the methodology employed the multinomial logit model. The model helped to determine the covariates that significantly affected the probability of transitioning from one labour-market state to another. The model advanced from the analysis based on Markov transition probabilities, which basically entailed a univariate relationship between a transition and a particular variable of interest (gender, for example). The multinomial logit model, on the other hand, provided a multivariate analysis of the probability of transitioning among states. Briefly, the specification of the model is as follows.
Suppose the ith investigated individual faces $j = \{1, 2, 3, \ldots, J\}$ events. In this study, the events were labour-market states. Thus, $j = 1, 2, 3$ (corresponding to employment, unemployment, and out-of-labour-market). Thus, the probability that a particular event occurs (employment, e.g.) can be obtained by estimating the parameters of a multinomial logit model. Mathematically, the probability that event j for the ith individual will occur is given by

[4] Given that a person was allowed to be in only one labour-market state in a given point in time, each row of the transition-probability matrix must sum to unity (see Clark & Summers, 1978).

$$P_{ij} = \frac{e^{\beta_j' z_{ij}}}{\sum_{j=1}^{J} e^{\beta_j' z_{ij}}} \qquad (01)$$

where P_{ij} is the probability of being in a particular labour-market state; z_{ji} includes the characteristics of the individual (such as age, education, etc.) that remain identical across the different labour-market positions; and β 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). In addition, given that the individual characteristics did 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 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 & Lewandowski, 2005).
If the last category, denoted by J, is the base category, then the coefficients for this outcome are set to zero. In this case, Equation 1 becomes:

$$P_{ij} = \frac{e^{\beta_j' z_{ij}}}{1 + \sum_{j=1}^{J-1} e^{\beta_j' z_{ij}}} \qquad (02)$$

because with $\beta_J' = 0$, then $e^0 = 1$.

In this context, the odds of outcome j occurring relative to the base outcome is given by:

$$\frac{P_{ij}}{P_{iJ}} = e^{\beta_j' z_{ij}} \qquad (03)$$

Taking the natural log of (3) expresses the MNL regression model as a MNL logit model.

4 Application and results

Empirical Analysis of Gabane's CBMS Data: Transition Probabilities
Descriptive Analysis

The CBMS study showed that Gabane's population was 6,842 in 2018. The total number of households whose members were interviewed was 2,693. The data showed there were more women (56.01%) than men (43.99%) in the study area. Further, we found that the majority of the population was young (15-39), as expected. They made up 55.4% of the total population, followed by those aged 0-14 (22.8%). Table 2 presents a profile of Gabane Village.

Table 2: Profile of Gabane Village

Total Population	6,842
No of households	2,693
Youth (15-39) % of Total Population	55.4%
Unemployed youth (2011 Population and Housing)	17.4%
Unemployed youth (CBMS Study)	26%
People living with disability	1.3%

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Our results showed very high rates of enrolment in both primary and secondary schools. Enrolment in primary education in Gabane was 98.6%, meaning that only 1.4% of children aged 6 to 12 (the age at which they would be expected to be enrolled in primary school) were left out. With regard to secondary schools, the enrolment rate was 98%, nearly equal to the primary-school-enrolment rate.

We determined the distribution of youth employment status as follows: The employed were those who, during a short reference period, did some work for either cash or in-kind payment; were self-employed for profit or family gain; or were temporarily absent from these activities but definitely planned to return to them (e.g., were on leave or sick). The second labour-market state was unemployed (individuals who did not do any work in the seven days prior to the study period and were aged 15-39; these were persons who did not work for payment in cash or in-kind, and/or were not self-employed for profit or family gain, and were demonstrably active in looking for a job in the previous thirty days). The third labour-market state was out-of-the-labor-force (persons defined by the fact that they held no job and/or were either not actively looking for a job or were not immediately available to work—i.e., they were neither employed nor unemployed). The analysis of transitions examined the proportion of those who were unemployed, employed, or out-of-the-labour-force and looked at the effects of gender and age on movement across labour-market positions.

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

Status	Jan/June 2016		July/Dec 2016		Jan/June 2017		July/Dec 2017	
	N	%	N	%	N	%	N	%
Employed	1700	44.7	1703	44.79	1871	49.21	1900	49.97
Unemployed	1556	40.92	1562	41.08	1441	37.9	1426	37.51
Out-of-Labor-Force	547	14.38	537	14.12	490	12.89	476	12.52
	3803		3802		3802		3802	

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

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

A gender breakdown of the labour market distribution appears in Tables 16 and 17 (see Appendix). As expected, higher unemployment and out-of-labor-force rates are found among women. These results depict the general problem in Botswana that women employment's and labor-participation rates are low (Statistics Botswana, 2018). About 51% of men were employed at the beginning of the study period, and this proportion increased to 57.5% by the end of the study period; conversely, 40% of women were employed in January-June 2016 with a smaller increase in the proportion to 44.3% in July-December 2017, compared to men's employment.
In order to better understand the determinants of youth unemployment across demographic groups, we computed the transition probabilities of individuals as they moved across the labour-market states of employment, unemployment, and out-of-the-labor-market; the results appear as follows:

Table 4 shows the transition probabilities and changes in the employment status for the whole cohort during the study period. For the period January-June 2016 to January-June 2017, we observed a 0.93 probability that those who were employed would remain 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 7.5%, which increased to 8% in the following period.
Further examination of those who were unemployed and out-of-the-labour-force in the previous period showed the transition probabilities of moving into employment of 18.8% and 2.2%, respectively. These probabilities increased to 20.4% and 3.9%, respectively, in the July-December 2016 and the July-December 2017 periods. The transition probabilities of moving into the state of unemployed from out of labor force state remained constant at 12.2% during the two periods of study

Table 4: Transition Probabilities for Overall Sample for the January-June 2016 to January-June 2017 and for July-December 2016 to July-December 2017

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.922	0.075	0.002
U	0.188	0.801	0.012
O	0.022	0.122	0.856
State/ period	July-December 2016 to July-December 2017		
	E	U	O
E	0.917	0.08	0.003
U	0.204	0.783	0.014
O	0.039	0.123	0.838

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Tables 18 and 19 (see Appendix) show transition probabilities calculated for men and women respectively. Similar patterns were observed for both men and women compared to the overall sample. The transition probabilities that those who were employed would remain in the employment state were 94.9% and 89.7%, respectively, for men and women in the January-June 2016 to January-June 2017 period. This transition probabilities slightly decreased by 0.5% for men and 0.6% for women in the July-December 2016 to July-December 2017 period. About 5% of the men who were employed transitioned to unemployment state during the two periods of study. The decline in the transition probabilities of those who remained unemployed and out-of-the-labour-market in the July-December 2016 to July-December 2017 was primarily because men who were unemployed (24.4%) and those who were out-of-the labour market (5.1%) moved into employment.Among women, however, the transition probabilities of moving from employment to unemployment were higher (10.2% vs. 4.8%, respectively). Further, we observed lower transition probabilities from unemployment to employment (17.9%) and from out-of-the-labour market to employment (3.1%), in the July-December 2016 to July-

December 2017 period. Women were more likely to lose employment than men and men had greater employment opportunities than women.

To further understand the labour-market situation in Gabane, we calculated the transition probability matrix for the 15-24, 25-34, and 35-39 age groups. For the youngest group, we observed higher transition probabilities of moving from the employment state to the unemployment state (18.5% and 17.4%) compared to the transition probabilities of moving into employment from unemployment states (13.1% and 15.1%) during the two periods of study. There was a substantial decline in the transition probabilities of moving from employment to the out-of-labour force (from 11.6% to 1.7%) during the study period.

Table 5: Transition Probabilities for 15-24 Year Olds

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-December 2016 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

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Table 20 (see Appendix) depicts the movements of the group aged 25-34. Compared to the younger age group, higher probabilities of moving from unemployment to employment state are observed (24.7% and 25.9%) during the two period of study. Conversely, lower transition probabilities of moving from employment state to unemployment state are observed. The probability of moving from out-of-the-labour-force to employment state decreased from 16.2% during the first period to 2.9% in the second period among the younger group whereas in the 25-34 age groups the transition probabilities increased from 7.8% to 12.5%, in the same period hence inversely influencing the transition probabilities of moving out-of-labor force state to employment state.

The labour-market-transition behavior of the older group (35 – 39 year olds) among youth is shown in Table 21 (see Appendix). For the two study periods, still lower transition probabilities of moving from employment state to unemployment state are recorded compared to the two younger groups. On further examination, the transition probability of moving from unemployment to employment increased from 18.4% to 20.1% though lower than the probabilities observed for the 25-34 age groups. Although there was no movement recorded from the out-of-labor-force to employment state in the first period of study, the transition probabilities for the same increased substantially to 33% in the second period of study. This group experienced higher employment rates compared to the other groups, but it was unclear whether employers preferred older, more experienced workers over younger, less experienced ones.

Tables 6-7 give the transition probabilities for education levels: primary and secondary. Although the probabilities of moving from employment to unemployment state increased for the primary level during the two periods of study (from 10.5% to 13.5%), the transition probabilities of moving from unemployment state to employment also increased (15.4% to 20%). There was no movement from employment to out-of-the-labour-force as well as from out-of-the-labour-force to employment state. The lack of movement from out-of-the-labour-force suggests some discouragement in searching for employment among the primary group.

Table 6: 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	0.827	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

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Table 7: 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	0.080	0.003
U	0.204	0.783	0.013
O	0.040	0.125	0.835

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Skill development is one area that is known to increase employability. Either through their employers or on their own, individuals commonly enrolled in skills-development training. The transition probabilities were calculated for individuals with training skills to understand whether training was a determinant of employment. Tables 8 and 9 show that, when we examined transitions from employment to unemployment for the two study periods, the transition probabilities of leaving employment were 7.4% and 9% respectively, In general, among those who attended training for 0-2 years (trainings were held once each year), the probabilities of finding a job increased for the unemployed (from 18.7% to 20.3%) and those out-of-the-labour market (from 2.2% to 3.9%)[5]. Some interesting results were obtained for the individuals who attended training 3-5 years, however. A pronounced 50% transition probability of moving from unemployment to employment was reflected during the first period of study, though the second period of study recorded no activity. Therefore, the second period of study showed no job opportunities for those who attended training 3-5 years. Perhaps those with skills chose to take up jobs in which they were skilled or a mismatch in the job market occurred.

Table 8: Transition Probabilities for Training Period: 0-2 years

State/ period	January-June 2016 to January-June 2017 E U O
E U O	0.923 0.075 0.002 0.187 0.801 0.003 0.022 0.122 0.856
State/ period	July-December 2016 to July-December 2017 E U O
E U O	0.917 0.080 0.003 0.203 0.783 0.014 0.039 0.123 0.838

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

[5] The category of 0-2 years in training includes people who received no training at all. Thus, the rise in the probability of finding a job for this group suggests that some who had no training also experienced an increased probability of finding a job. While this interpretation is logical, it seems untenable in the context of prevailing high unemployment in Gabane Village. A more plausible interpretation is that the increase in the probability of finding a job for this group reflected more of the effect of improved chances of finding a job among those who had received 1-2 years of training.

Table 9: Transition Probabilities for Training Period: 3-5 Years

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

The behaviour of job seekers during the time of labor participation was important in the market analysis. Participation in government programmes offered employment opportunities for those who were qualified and applied. A transition probability of moving from unemployment to employment of about 61.9% was realized during the first period of study and then increased to 64.3% in the subsequent study period. Surprisingly, there were no employment opportunities for those who were out-of-labor-force during the whole study period and higher transition probabilities of moving from employment to unemployment state. Lack of participation in government programs brought lower employment opportunities. There was an 18.3% probability of moving from unemployment into employment during the first period of study and it increased to 19.4% in the next period. Compared to those who did not participate in government programmes, the risk of losing jobs for those who participated in government programmes was high at 15.4% and 18.2%, respectively, during the first and second period of the study. Those who did not participate in programs experienced lower job losses at 7.5% and 8% in the first and second period of study, respectively, (see Tables 10 and 11). These findings may suggest either the lack of sustainability of the programs or the poor management of the programs.

Table 10: Transition Probabilities for Programme Participation

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

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Table 11: Transition Probabilities for Non-Participants in Programme

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.929	0.075	0.002
U	0.183	0.809	0.012
O	0.022	0.121	0.856
State/ period	**July-December 2016 to July-December 2017**		
	E	U	O
E	0.924	0.080	0.003
U	0.194	0.785	0.014
O	0.039	0.121	0.838

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Table 12 gives transition probabilities matrix of moving from formal employment to informal employment and vice-versa. During the first period of study transition probabilities of 1.7% and 8.3% of moving from formal to informal employment and to unemployment states respectively. The subsequent period showed a slight increase in those probabilities. On the other hand, we recorded transition probabilities of only 1.2% and 6.6% of moving from informal employment to formal and from informal to unemployment states, respectively. These probabilities increased to 1.5% and 7.9% respectively in the next period of study. Despite the low transition probabilities, the study showed better opportunities of joining both formal and informal employment from out-of-labor market of 10,4% and 8.4% respectively in the first period and 10.9% and 9.5% respectively in the subsequent period. These transition probabilities seem to suggest higher chances of moving from formal-sector employment to informal-sector employment or unemployment than from informal-sector jobs to formal-sector jobs or unemployment. This made sense because entering the formal-sector employment required higher educational qualifications, although the education variable (see the MNL model results, below) was not statistically significant in explaining the transitions of Gabane youth across the three labour-market states. On the other hand, entering informal-sector employment was relatively easier because it required fewer educational qualifications.

Table 12: Transition Probabilities from Formal to Informal Sectors

State/ period	January-June 2016 to January-June 2017 FE IE U O
FE IE U O	0.899 0.017 0.083 0.002 0.012 0.919 0.066 0.003 0.104 0.084 0.801 0.012 0.011 0.011 0.122 0.856
State/ period	July-December 2016 to July-December 2017 FE IE U O
FE IE U O	0.901 0.016 0.082 0.002 0.015 0.902 0.079 0.004 0.109 0.095 0.783 0.014 0.019 0.020 0.123 0.838

Note: FE=Formal Employment; IE- Informal Employment.
Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Discussion of results

In summary, the transition probabilities of remaining in same state were inflexible across all states for most of the variables. This means that the probabilities of moving either from employment to unemployment or from unemployment to employment increased slightly during the study period—i.e., there were high levels of persistence among Gabane youth in each of the three labour-market states.

Some interesting findings included the following: Young men in Gabane experienced higher employment opportunities than did women. With respect to the three age groups, 25-34 year olds experienced high employment rates compared to the 15-24 and 35-39 groups. Furthermore, secondary-school leavers experienced higher employment opportunities compared to primary school leavers. Employment opportunities were higher during the first period of the study for those who attended training for 3-5 years (i.e., once per year). Participation in government programs offered employment opportunities for those who were qualified and applied. Finally, entering the informal-sector employment was relatively easier because it required fewer educational qualifications, suggesting that the government should focus on developing the informal sector where greater job opportunities exist.

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

The analysis of labour transitions in terms of flow frequencies, presented above, was limited in the sense it did not permit robust determination of the impact of individual factors on the chances of finding or losing a job. Rather, the analysis captured transitions between labour-market states resulting from the joint influence of all variables (see Bukowski & Lewandowski, 2005). In order to delineate individual factors that influenced people's transition decisions, a multiple regression model was required.

We employed a multinomial logit (MNL) model to analyse changes in labour-market states in Botswana. MNL was suitable for this task because it modelled the outcome variable as unordered categories, just as transitions across the labour-market states (employment, unemployment, and out-of-the-labour market) were not ordered. The working of the labour market, in response to factors determining labour-market decisions, was such that by the end of the transition period,[6] an employed person may have continued to be employed or may have moved either to the unemployment pool or to the out-of-labour-market 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.

[6] There were two transition periods in the survey data: January-June 2016 to January-June 2017 and July-December 2016 to July-December 2017.

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

Prior to presenting model parameter estimates, a description of the model variables and summary of key variables is important. **Table 13** presents description of variables.

Table 13: Description of Variables

Variable	Variable Coding	Notation in Model
Gender	Dummy variable 1 if men	gender (women=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 Southeast 1 if in Gabane Southwest 1 if in Gabane Northwest 1 if in Gabane Northeast	 local1 (=base category) local2 local3 local4

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

The variables in Table 13, which involve characteristics and variables related to economic conditions, were all used in an MNL regression model (with their short names shown in the third column of the table).

Table 14 presents MNL regression estimates, indicating the individual factors that influenced decisions on labour transitions among the three states between January-June 2016 and January-June 2017 (Panel A) and between July-December 2016 and July-December 2017 (Panel B).

In Table 14, the dependent variable is labour-market state, which represents the three states in our study: employment, unemployment, and out-of-the-labour-force. The normalisation of the model expressed the dependent variable as the probability of occurrence of the employment state (E) or the out-of-the-labour-force state (OLF) relative to the probability of occurrence of the unemployment state (U) referred to as the base category.[7]

In Panel A the results showed that, between January-June 2016 and January-June 2017, the multinomial log-odds for becoming employed relative to remaining unemployed increased by 0.446 units for men (as compared to women), all other things being equal. The Z-statistic showed that this effect was highly statistically significant, even at the 1% level. On the other hand, although men were more likely to exit the labour force, this was not statistically significant.

Being an older youth (relative to the base age of 15-24) increased the likelihood of finding employment versus remaining unemployed. Consistent with this result, being an older youth reduced the likelihood of exiting the labour force when unemployed, all other things being equal.

Higher levels of education and training of youth, relative to the base of pre-school education, was only indicative of promoting employment relative to the base of unemployment status, as these terms were not statistically significant. For example, the coefficients of the education and training were positive, suggesting a rise in the log-odds of obtaining employment versus unemployment, but the coefficients were not statistically insignificant. A broadly similar result held when considering movement from the unemployment state to the out-of-the-labour-force state.

The economic factor of remuneration (in cash) increased the log-odds of being employed rather than remaining unemployed by 0.0001 units, all other conditions holding equal. Consistently, higher remuneration reduced the probability of exiting the labour force by a similar magnitude. This finding seemed to suggest that higher remunerations encouraged youth to enter the labour market and obtain employment rather than to remain unemployed. A possible corollary was that, in response to low remuneration, some were discouraged from entering the labour market and obtaining jobs.

Another notable result was that participation in government labour-market programmes significantly increased the probability of being employed versus unemployed. Participation in labour-market programmes was not statistically significant in the transition from unemployment to the out-of-labour-force state.[8]

Lastly, a location effect was found in the transition probabilities of youth across labour-market states in Gabane Village. Our results suggested that residing in the Gabane Northeast Ward (compared to the reference ward of Gabane Southeast) increased the likelihood of employment relative to unemployment. Apparently, as this happened, the

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

[8] A specification designed to investigate the contribution of labour-market programmess to decisions to move among labour-market states yielded no useful results because those who participated in such programmess were too few to allow model estimation of their transitions (the results are available upon request).

likelihood increased that youth would join the labour force from the out-of-labor-force state, but this occurred through a direct link from out-of-labor-force to employment because the probability of transition from unemployment to out-of-labor-force increased. On the other hand, residing in Gabane Northwest and Southwest compared to being in Gabane Southeast reduced the probability of exiting the labour force.

Table 14: Multinomial Model of Estimation of Transition Probabilities

Predictor Variables	**Panel A**		**Panel B**	
	Jan-Jun2016 to Jan-Jun2017		**Jul-Dec2016 to Jul-Dec2017**	
	From U to E	**From U to OLF**	**From U to E**	**From U to OLF**
Gender	0.446 (4.67)***	0.141 (1.18)	0.517 (5.33)***	0.100 (0.83)
ageyr2	1.360 (12.10)***	-2.247 (-12.84)***	1.273 (11.28)***	-2.228 (-12.60)**
ageyr3	1.716 (12.16)***	-3.765 (-6.39)***	1.606 (11.29)***	-3.728 (-6.32)***
edu2	0.161 (0.30)	-0.165 (-0.18)	-0.032 (-0.06)	-0.298 (-0.32)
edu3	0.712 (1.51)	-0.337 (-0.39)	0.497 (1.05)	-0.388 (-0.45)
edu4	0.056 (0.12)	0.038 (0.04)	-0.109 (-0.23)	-0.089 (-0.10)
wagcshm	0.0001 (22.02)***	-0.0001 (-5.47)***	0.0001 (22.49)***	-0.0001 (-5.51)***
Lmktprog171	1.371 (3.17)***	-16.364 (-0.01)	1.298 (3.29)***	-1.233 (-1.15)
local2	-0.020 (-0.16)	-0.683 (-4.66)***	-0.006 (-0.05)	-0.654 (-4.43)***
local3	0.102 (0.82)	-0.701 (-4.07)***	0.029 (0.23)	-0.780 (-4.45)***
local4	0.399 (2.62)**	0.791 (4.62)***	0.416 (2.68)**	0.777 (4.48)***
constant	-2.679 (-5.46)***	0.128 (0.15)	-2.450 (-4.99)***	0.201 (0.23)
Number of obs = 3,788 Log likelihood = -2.384.17 LR Chi2(22) = 2761.10			Number of obs = 3,788 Log likelihood = -2278.34 LR Chi2(22) = 2831.36	

Prob > Chi2 = 0.0000 Pseudo R2 = 0.3714	Prob > Chi2 = 0.0000 Pseudo R2 = 0.3832

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.
Notes:

(i) The values in parentheses are Z-statistics.
(ii) ***significant at 1%; ** significant at 5%.

In Panel B the results associated with the two MNL equations for the outcomes of employment and out-of-the-labour-force were quite similar to those obtained in Panel A. Thus, the interpretation above also applies to the results in Panel B.

There was a possibility that women faced different experiences with respect to such factors as education, income, and employment status. In this context, it was expedient to estimate the MNL model separately for men and women. Table 22 (see Appendix), presents results for women.

In terms of the statistical significance of age, cash wages, and labour-market-programme variables, the results in Table 22 (see Appendix) seem quite similar to those obtained when we estimated the MNL model for men and women together. The similarity in results prevailed even in the case of the location effect. Differences can be observed, however, in the magnitude of increases in the multinomial log-odds for the variables age and Lmktprogram171.

The results obtained from estimating the model for men are presented in Table 23 (see Appendix). As with the results in Table 22 (see Appendix), the results obtained from estimating the MNL model for men were similar to those obtained using both men and women together. The findings in the table indicate that the extent to which young women in Gabane faced different experiences with respect to such factors as education, income, employment status (observed in the results for the Markov Chain model and in terms of the coefficient of the gender variable in the MNL model) was discernible in the magnitude of the probabilities of moving across labour-market states and not in the signs of coefficients and/or statistical significance.

The main difference in results between men and women was the location effect on the transition probabilities of youth across labour-market states in Gabane Village. The regression specified for women, similar to the regression model aggregated over men and women, indicated a significant location effect for youth in the Southwest and Northwest vs. Southeast Wards. However, in the regression for men, the location effect was absent. The only result that persisted, from the aggregated model through the regression model for women and for men, was the location effect associated with Gabane Northeast. The results suggested that residing in the Gabane Northeast Ward (compared to the reference ward of Gabane Southeast) increased the likelihood of employment relative to unemployment. It seems that as this happened, the likelihood increased that youth would join the labour force from out-of-labor-force status. Living in Gabane Northwest and Southwest, compared to living in Gabane Southeast, however, reduced the probability of exiting the labour force.

In making comparison between the results from the MNL model and results of analyses of transition probabilities (from the Markov model), we observed consistency in the empirical results. In particular, older compared to younger youth, as well as men compared to women, had higher chances of employment (or remaining employed). (As already stated, the latter result did not seem robust.) Consistency also prevailed in the programme participation variable. In the case of participation in the government programmes, the discernible positive effect of programme participation on transition probabilities seemed 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 unemployment to the out-of-labour-market state showed similar signs and significance, as was the case for the relative log-odds of moving from unemployment to employment for age and income. The difference lay in the relative log-odds for exiting the labour force as individuals' education level increased and in participation in government programmes which, although the signs were correct, was statistically insignificant at the 5% level. Similarly, the training variable still had a positive coefficient, suggesting that a one-unit increase in training increased the relative log-odds of exiting the labour market compared to being employed.

In conclusion, more men than women in Gabane tended to remain employed and were less likely to lose their jobs or to exit the labour market, and the same trend held true for older youth and for individuals with higher incomes. However, young people with more training tended to become unemployed and/or to exit the labour market. Meanwhile, the education/training level of young people in Gabane seems not to have influenced transition probabilities across different labour-market states.

To establish the robustness of the empirical results, the labour-market state was decomposed into formal employment and informal employment, given that the questionnaire allowed respondents to provide such information. The results obtained in this regard are presented in Table 15.

It was apparent that the results obtained after decomposing employment (formality vs. Informality) were very similar to those obtained when employment was aggregated. The similarity can be observed in the signs of the coefficients of the predictors and the statistical significance of the coefficients. Hence, the results obtained prior to decomposition of employment were robust to model-specification changes.

Nevertheless, there were slight changes in terms of the magnitude of coefficients, possibly reflecting differences in the difficulty of moving from unemployment (the base) to formal employment versus moving to informal employment. For example, in the model that considered aggregate employment, the multinomial log-odds of becoming employed relative to remaining unemployed increased by 0.446 units for men versus women, assuming other conditions remained the same. When employment was disaggregated into formal and informal jobs, the increase in the log-odds for this gender variable became only 0.246 for formal employment and was much larger (0.601) for informal employment. The possibility exists that this difference in magnitudes of log-odds implied that young men found it easier to move to informal employment than to formal employment.

A similar phenomenon seemed to occur with regard to the age variable. In the case of both aggregate employment and disaggregated employment, we noted that the increase in the log-odds of moving from unemployment to employment was larger in the 35-39-year-old group (denoted by ageyr3 in the model), as compared to the base of 15-24, than it was in the 25-34-year-old group) denoted by ageyr2 in the model). However, we further noted that comparing formal employment and informal employment allowed the observation that the increase in log-odds was smaller for the 25-34-year-old group while it was larger for informal employment in the case of the 35-39-year-old group. This outcome probably indicates that it was relatively difficult for younger youth to move to informal employment, because they had less exposure to market opportunities. At the same time, it was less difficult for older youth (35-39 compared to the base of 19-24 and to those aged 25-34) to move to the informal sector because they had more exposure to market opportunities.

Table 15: Multinomial Model of Estimation of Transition Probabilities from January-June 2016 to January-June 2017

Predictor Variables	Transitions from Unemployment to:					
	Formal Employment		**Informal Employment**		**Out-of-the-Labour-Force**	
	Coefficient	*Z-value*	*Coefficient*	*Z-value*	*Coefficient*	*Z-value*
Gender	0.246	(2.19)**	0.601	(5.69)***	0.146	(1.22)
ageyr2	1.433	(10.09)***	1.311	(10.00)***	-2.248	(-12.83)***
ageyr3	1.654	(9.56)***	1.762	(11.12)***	-3.758	(-6.38)***
edu2	0.040	(0.06)	0.269	(0.46)	-0.163	(-0.18)
edu3	0.905	(1.46)	0.603	(1.18)	-0.338	(-0.39)
edu4	0.295	(0.47)	-0.105	(-0.20)	0.037	(0.04)
wagcshm	0.0001	(24.17)***	0.0001	(18.45)***	-0.0001	(-5.52)***
Lmktprog171	1.898	(4.12)***	0.673	(1.22)	-13.491	(-0.03)
local2	-0.117	(-0.84)	0.077	(0.56)	-0.682	(-4.66)***
local3	-0.103	(-0.70)	0.284	(2.00)**	-0.699	(-4.06)***
local4	-0.536	(-2.88)***	0.931	(5.75)***	0.806	(4.70)***
constant	-3.575	(-5.60)***	-3.281	(-6.14)***	0.125	(0.14)
Number of obs = 3,788 Log likelihood = -3438.68 LR Chi2(22) = 3111.99 Prob > Chi2 = 0.0000 Pseudo R2 = 0.3115						

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.
Notes: *** means significant at 1%** significant at 5%.

5 Conclusions and policy implications

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

The analysis of transition probabilities indicates that men had higher probabilities than women of remaining employed or of moving from the unemployment state to employment. This differential response between men and women obtained even after disaggregating the analysis by estimating separate models for men and women. Although the difference was unobservable with respect to the signs of coefficients (and their levels of significance), it did occur in the magnitude of probabilities that men would transition from unemployment to employment versus the magnitude of probabilities that women would make the same transition. Similar differences in the magnitude of probabilities for men and for women were observed in transitions from unemployment to the out-of-labour-market state.

Our transition probabilities suggested that, in general, older youth had higher probabilities of remaining in the employment state or of moving from unemployment to employment compared to younger youth. It was encouraging that the findings in the context of the MNL model were consistent with those in transition probabilities. In addition, the MNL model results indicated that youth with higher cash wages or who participated in the government labour-market programmes faced higher probabilities of remaining in employment or of moving from unemployment to employment, as compared to those with lower wages or who did not participate in government programmes. The positive impact relating to participation in government programmes was noteworthy, given the fact that survey data indicated that the majority of the Gabane youth (3,767 of 3,802, or about 99.26%) did not participate in them in 2017. Only twenty-eight youth (about 0.74%) participated in the five government programmes (the Youth Development Fund, the National Service Programme, the Young Famers Fund, the National Internship Programme, and the Government Voluntary Scheme).

The regression model results also suggested that education had no effect on the transition from unemployment to employment—that is, the education variable was not statistically significantly different than zero. This suggests need for improvements to the education system, particularly at the secondary and tertiary levels, so as to provide education and training that meet the needs of industry.

The following table provides our key findings, policy implications, and policy recommendations.

Table 16: KEY FINDINGS, POLICY IMPLICATIONS, AND RECOMMENDATIONS

KEY FINDING	POLICY IMPLICATIONS	RECOMMENDATIONS
1. Men, compared to women, had higher probabilities of remaining employed or moving from unemployment state to employment	Women have fewer job opportunities as a result of limited jobs, occupational segregation, and (perhaps) skills mismatch from training and education.	– The government, businesses, financial sector, and NGOs should prioritize investment in segments and sectors where women workers are concentrated in Gabane Village. – The stakeholders (government, NGOs, and businesses) should also encourage self-employment and entrepreneurship for women in Gabane Village. They should be supported with relevant programmes to improve the quality and efficiency of the regulatory framework for business registration and create support and mentorship, including facilitating access to credit and providing business knowledge, financial services, and technical assistance to help in the development of micro- and small businesses. – Adopt community-driven employment strategies through local participation and community-owned interventions.
2. Older youth had higher probabilities of remaining in the employment state or of moving from unemployment to employment, compared to younger youth	There is need to provide more experience for youth during and after education and training.	– Establish a youth unemployment task force at the community level that includes representatives of employers, education, and trade unions. This task force should try to promote cooperation among all stakeholders by encouraging the private sector to create jobs for youth and collect best practices. – There should be entrepreneurship

		education, meaning an initiative that brings the public and private sectors together to provide young people in primary and secondary schools and early university with high-quality education programmes to teach them about enterprise, entrepreneurship, business, and economics. – Through a Vocational and Education Training Pact, government, employers, and business associations can be involved in the training of youth by establishing a set target of apprenticeship placements and by enhancing entrance qualifications to improve core employability skills. Quality education and post-secondary practical training coupled with a set of key competencies will increase youth employability. – Enhance employability skills of new graduates by improving the connection between higher education curricula and the demands of the labour market.
3. The majority of Gabane youth (99%) did not participate in any government employment programme in 2017. Youth who participated in government labour-market programmes faced higher probabilities of remaining in employment or of moving from the unemployment state to employment, as compared	Government employment programmes are not accessible to youth because of lack of knowledge and/or complexities in the processes of access. Youth who participated in government programmes have more chances of moving from	– Publicise government youth programmes, especially at the community level, in different council wards, and at the main kgotla; an elected youth council and committees of young policy advisors should empower youth in the communities. – Stakeholders (government, businesses, non-profit organizations) should develop entrepreneurship in the community by providing free training courses for potential entrepreneurs on how to

to those with lower wages or who did not participate in government programmes.	the unemployment and out-of-the-labour-force states to employment or to self- employment.	conduct market research and refine business plans before presenting to the approval body. – Simplify programme forms and other qualification criteria for funding; for instance, translate the programme forms from English to the local language (Setswana) and provide orientation on application guidelines and forms.

References

Ama. N.O (2008). Transition from Higher Education to Employment: A Case Study of Graduates of Faculty of Social Sciences, University of Botswana. *Educational Research and Review, 3*(8), 262-274.

Arif, G. M., Khan Kiani, M. F., and Sheik, K.H. (2002). Labour Market Dynamics in Pakistan: Evidence from the Longitudinal Data. *The Pakistan Development Review, 41*(4-Part II), 701-720. Available at https://pdfs.semanticscholar.org/6fa4/f5c3c0956c5460f5b445f9e823c4ffb74da0.pdf.

Audus, R., Berde, E., and Dolton, P. (2005). Youth Unemployment and Labour Market Transitions in Hungary. *Education Economics, 13*(1), 1-25.

Bosch, M. and Maloney, W. (2007). Comparative Analysis of Labour Market Dynamics Using Markov Processes: An Application to Informality. *Labour Economics, 17*(4), 621-631.

Bosler, C. and Petrosky-Nadeau, N. (2016). Job-to-Job Transitions in an Evolving Labor Market. *Federal Reserve Bank of San Francisco Economic Letter*, 34. Available at https://www.frbsf.org/economic-research/publications/economic-letter/2016/november/job-to-job-transitions-in-evolving-labor-market.

Bukowski, M. and Lewandowski, P. (2005). Assessing Flows out of Employment in Poland: Evidence from Multinomial Logit Analysis. *Labor and Demography* 0511007, University Library of Munich, Germany, revised 30 Nov 2005. Available at https://econwpa.ub.uni-muenchen.de/econ-wp/lab/papers/0511/0511007.pdf.

Cilasun, S. M., Acar, E. O., and Gunalp, B. (2015). The Effects of Labor Market Reforms on the Labor Market Dynamics in Turkey. MPRA Paper No. 64767. Munich, Germany: Munich Personal RePEc Archive. Available at https://mpra.ub.uni-muenchen.de/64767.

Clark, K.B. and Summers, L.H. (1978). Labor Transitions and Unemployment. NBER Working Paper No. 277. Cambridge, MA: National Bureau of Economic Research.

Cuesta, C. and Bohorquez, C. (2014). Labour Market Transitions and Social Security in Columbia. *The Journal of Developing Areas*, *48*(3), 149-174

Fabrizi, E. and Mussida, C. (2009). Determinants of Labour Market Transitions. *Giornale degli Economisti e Annali di Economia*, *68*, 233-265.

Foley, M.C. (1997). Labour Market Dynamics in Russia, Center Discussion Paper No. 780. Center Discussion Paper No. 780. New Haven, CT: Yale University, Economic Growth Center.

Kavuma, N.S., Morrissey, O., and Upward, R. (2015). Worker Flows and the Impact of Labour Transitions on Earnings in Uganda, Discussion paper 2015-01. University of Nottingham, Centre for Research in Economic Development and International Trade.

Kemiso, O. and Kolawole, O.D. (2017). Energetic But Jobless: Socio-Economic and Institutional Drivers of Youth Unemployment in the Okavango Delta, Botswana. *Botswana Notes and Records, 49*(1), 154-167.

Kucharski, L. and Kwiatkowski, E. (2006). Multinomial Logit Model and its Application in the Labor Market Position Analysis of Individuals in Poland. *Acta Universitatis Lodziensis, Folia Oeconomica*, No 196. Available at http://cejsh.icm.edu.pl/cejsh/element/bwmeta1.element.hdl_11089_17518

Mahoney, T. A. and Milkovich, G. T. (1971). *Techniques for Application of Markov Analysis to Manpower Analysis*. Minneapolis: Industrial Relations Center, University of Minnesota.

Nthomang and Diraditsile, Kabo (2015). Youth Unemployment in Botswana: Understanding the Journey Traveled So Far. *Journal of the Botswana Education Research*, *19*, 45-55.
Siphambe, H., Bakwena M., Setlhare, L., Kolobe, M., Oageng, I., Setlhare, K., and Motswagae, T. (in press). CBMS Design Paper: Case Study of Gabane Village in Kweneng District in Botswana.
Statistics Botswana (2018). 2015/16 Botswana Multi Topic Household Survey. Gaborone, Botswana.
Steiner, V. and Kwiatkowski, E. (1995). The Polish Labour Market in Transition. Discussion Papers, No. 95-03. Mannheim, Germany: Zentrum für Europäische Wirtschaftsforschung (ZEW).
Taşçı, H. M. and Tansel, A. (2005). Unemployment and Transitions in the Turkish Labor Market: Evidence from Individual Level Data. IZA Discussion Paper No. 1663. Bonn, Germany: Institute for the Study of Labor (IZA).
Van der Merwe, M. (2016, December). Factors Affecting an Individual's Future Labour-market status. Reserve Bank of Australia 11-22. Available at https://www.rba.gov.au/publications/bulletin/2016/dec/pdf/rba-bulletin-2016-12-factors-affecting-an-individuals-future-labour-market-status.pdf.
Voicu, A. (2002). Labour Force Participation Dynamics in the Romanian Labour Market. William Davidson Institute Working Paper No. 481. Ann Arbor, MI: William Davidson Institute, University of Michigan.

Annex

This section should report additional tables and figures that are not included in the main text.

Table 16: Distribution of Sample Labor Market States for Gabane Youth (Men)

Status	Jan/June 2016		July/Dec 2016		Jan/June 2017		July/Dec 2017	
	N	%	N	%	N	%	N	%
Employed Unemployed Out-of-Labor-Force	834 577 221	51.10 35.36 13.54	832 585 215	50.9 8 35.8 5 13.1 7	917 512 203	56.1 931. 37 12.4 4	939 500 193	57.54 30.64 11.83
	1632		1632		1632		1632	

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Table 17: Distribution of Sample Labor Market States for Gabane Youth (Women)

Status	Jan/June 2016		July/Dec 2016		Jan/June 2017		July/Dec 2017	
	N	%	N	%	N	%	N	%
Employed Unemployed Out-of-Labor-Force	863 972 326	39.94 44.98 15.09	869 970 322	40.2 1 44.8 9 14.9 0	951 923 287	44.0 1 42.7 1 13.2 8	958 920 283	44.33 42.57 13.10
	2161		2161		2161		2161	

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Table 18: Transition Probabilities for Men for the period January-June 2016 to January-June 2017 and July-December 2016 to July-December 2017

State/ period	January-June 2016 to January-June 2017		
	E	U	O
E	0.949	0.048	0.004
U	0.213	0.771	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

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Table 19: Transition Probabilities for Women for the January-June 2016 to January-June 2017 and July-December 2016 to July-December 2017 Periods

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/ 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	0.134	0.835

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Table 20: Transition Probabilities for 25-34 Year Olds

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

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

Table 21: Transition Probabilities for 35-39 Year Olds

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

Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

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

Predictor Variables	Transitions from Unemployment to:			
	Employment		**Out-of-the-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. Log likelihood = -1315.89 LR Chi2(22) = 1655.27 Prob > Chi2 = 0.0000 Pseudo R2 = 0.3861				

Notes: *** significant at 1%; ** significant at 5%.
Source: Authors' calculations using CBMS Census 2018, Gabane Village, Botswana.

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

Predictor Variables	**Transitions from Unemployment to:**			
	Employment		**Out-of-the-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	(-0.02)
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 Log likelihood = -993.75 LR Chi2(22) = 1099.57 Prob > Chi2 = 0.0000 Pseudo R2 = 0.3562				

Notes: *** significant at 1%; ** significant at 5%.