Reservation wages, transitions from, and the duration of, unemployment in South Africa

By Minette Haasbroek

Student number: 2009055654

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Department of Economics and Finance

University of the Free State (Bloemfontein Campus)

Supervisor: Mr Jean-Pierre Geldenhuys

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Declaration

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(2009055654)

Abstract

South Africa has one of the highest unemployment rates in the world, with women, youths, and people with low levels of education being especially likely to be unemployed. Most South African unemployed are also long-term unemployed. Persistently high unemployment and high long-term unemployment rates have substantial negative socio-economic implications. This study investigates the effect of reservation wages on transitions from unemployment and the duration of unemployment. Furthermore, the effects of age, education and gender on unemployment transitions and unemployment duration are also assessed. South African household survey panel data from the third (data collected in 2012) and fourth (data collected in 2014 and 2015) waves of the National Income Dynamics Study (NIDS) were used to this end. In addition to descriptive statistics (transition matrices, proportions/frequencies and means), discrete choice models (binomial and multinomial logits and probits) for unemployment transitions, as well as discrete choice models (binomial logit and probit) for unemployment duration were estimated. Discrete choice models were chosen as the appropriate method due to the nature of the available data.

The descriptive statistics and the results of the discrete choice models indicated that higher reservation wages were associated with higher probabilities to transition to employment and to inactivity relative to remaining unemployed. People with higher reservation wages were less likely to be long-term unemployed. These results contradict the theoretical job search theory, a possible suggestion for this occurrence is that those that transitioned to employment had individual characteristics that justified higher reservation wages and those that transitioned to inactivity had unrealistic reservation wages given their individual characteristics. Age, education, and gender were also found to be associated with both unemployment transitions and unemployment duration. Generally, age was positively associated with transitions to employment, transitions to inactivity and long-term unemployment, indicating that older workers were more likely to become employed or become inactive relative to staying unemployed and those who remained unemployed were more likely be long-term unemployed. People with higher levels of educational attainment were more likely to transition to employment, while those with lower levels of educational attainment were more likely to transition to inactivity. While the descriptive analysis showed that those with higher levels of educational attainment were generally less likely to be long-term unemployed, this result was not evident in the duration regressions. Men were more likely to transition to employment and less likely to transition to inactivity than women. Women were more likely to be long-term unemployed. To increase transitions to employment, decrease transitions to inactivity and to decrease long-term unemployment, policymakers must target vulnerable groups like women, and the youth. Higher educational attainment, especially the completion of secondary education, may also play a critical role in helping unemployed individuals to transition to employment and lower the duration of their unemployment spells.

Key words: unemployment, South Africa, transitions from unemployment, duration of unemployment, reservation wages, age, gender, level of education.

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Chapter 1: Introduction

1.1 Introduction

In this chapter, I will discuss the background and motivation for the study, present the problem statement, outline the research aim and objetives, and provide an outline for the chapters to follow.

1.2 Background and motivation

Unemployment in South Africa is very high and a high proportion of the unemployed are long-term unemployed. The major concerns arising from long spells of unemployment are the associated decreases in human capital levels and the increase in poverty (Möller, 1990; Kingdon and Knight, 2004; Lollivier and Rioux, 2010; Frijters and van der Klaauw, 2006).

Unemployment is high and persistent in South Africa: Table 1.1 below shows the unemployment rate for the searching and non-searching unemployed. The statistics are reported for the second quarters of 2012, 2015, 2019 and 2021. During the second quarters of 2012 and 2015, field workers were collecting data for the third and fourth waves, respectively, of the National Income Dynamics Study (NIDS), which is the data that is used in this study, while the data from 2019 are reported to provide a pre-covid view and 2021 figures reflect the most recent estimates of the unemployment rate at the time of writing.

Table 1.1 Searching and non-searching unemployment rates in South Africa, 2012, 2015, 2019 and 2021

	2012	2015	2019	2021
Searching unemployment rate	24,9%	25,0%	29,0%	34,4%
Non-searching unemployment rate	36,2%	34,9%	38,0%	44,4%

Source: Stats SA Quarterly Labour Force Survey (Quarter 2 2012, Quarter 2 2015, Quarter 2 2019 and Quarter 2 2021).

In the second quarter of 2019, the searching and non-searching unemployment rates, were 29% and 38%, respectively (Stats SA, 2019). The table shows that South African unemployment is very high, and very persistent. The much higher 2021 values reflect the effects of the COVID-19 pandemic, as well as the lockdown regulations that have been imposed from 2020 onwards. Unemployment in South Africa is very high compared to other countries. For example, in 2020, fellow BRICS countries had the following unemployment rates: Brazil 13,7%; Russia 5,7%; India 7,1% and China 5,0% (World Bank, 2021).

Table 1.2 below shows South African (searching) unemployment rates by gender, age and level of education.

Table 1.2 Searching unemployment rates by gender, age and level of education, South Africa, 2012, 2015, 2019 and 2021

	2012	2015	2019	2021
Gender				
Men	27.5%	23.1%	26.1%	32.4%
Women	22.8%	27.3%	31.3%	36.8%
Age				
15-24 years	51.5%	49.9%	56.4%	64.4%
25-34 years	29.3%	29.9%	35.6%	42.9%
35-44 years	17.8%	19.0%	23.3%	29.4%
45-54 years	12.5%	14.1%	17.2%	21.0%
55-64 years	6.4%	8.0%	10.5%	12.5%
Education levels				
Less than matric	29.3%	29.6%	34.5%	39.1%
Matric	26.3%	25.6%	29.4%	36.6%
Tertiary	9.4%	11.5%	14.5%	18.8%

Source: Stats SA Quarterly Labour Force Survey (Quarter 2 2012, Quarter 2 2015, Quarter 2 2019 and Quarter 2 2021) and author's own calculations.

The table shows a substantial increase in the unemployment rates between 2015 and 2021, the 2019 figures are provided as a pre-covid baseline. Furthermore, across all periods, women have higher rates of unemployment than men, while unemployment rates decrease sharply with increased age and level of educational attainment.

In the second quarter of 2021, more than 76% of the unemployed were long-term unemployed, while almost 68%, almost 64% and more than 71% of the unemployed were long-term unemployed in the second quarters of 2012, 2015 and 2019, respectively (Stats SA, 2012; 2015; 2019; 2021). The unemployment statistics provided by Statistics South Africa in its Quarterly Labour Force Survey (QLFS) differentiate between those who have been unemployed for less than 12 months, and those who have been unemployed for more than 12 months. Statistics South Africa and the OECD define long term unemployment as being unemployed for 12 months or more (OECD, 2018), while the Bureau of Labour Statistics in the United States regard long term unemployment as being unemployed for more than 27 weeks, i.e. more than 6 months (Kosanovich and Sherman, 2015).

The Labour Market Dynamic Study (2020) published by Statistics South Africa provides a breakdown of long-term unemployment. Women are more likely to be long-term unemployed than men. In 2019, 75% of unemployed women were long-term unemployed, compared to 67% of unemployed men (Stats SA, 2020). According to the report, the age group 15-24 years had the lowest share of long-term unemployed (65%). The other age groups only had marginal differences in their incidence of long-term unemployment (between 72,4% and 73,4%). The report also indicated that people with higher levels of education were less likely to be long-term unemployed, as the largest share of long-term unemployed are people who did not complete secondary school.

The South African government has initiated numerous capacity building and policy initiatives to address the high unemployment rate, but without much success (Nattrass, 2014). The focus on unemployment, amongst other things, featured in the first large-scale initiative of the new democratic government of South Africa in 1994, the Reconstruction and Development Plan (RDP). The Medium Term Strategic Framework in 2009 aimed to halve unemployment by 2014, however the unemployment rate actually increased over this period from 23,5% to 24,9%. In 2012, the National Development Plan (NDP) was introduced, which targets an unemployment rate of 6% by 2030 (Fourie, 2013). Nine years after the adoption of the NDP, the unemployment rate is still increasing, indicating that understanding and combating unemployment has become even more important.

The prevalence of unemployment has wider socio-economic implications. The effects of unemployment on inequality (Tregenna, 2011; Anand, Kothari and Kumar, 2016), poverty, economic welfare, crime, social instability, health and human capital are well known (Kingdon and Knight, 2004; Nattrass and Walker, 2005). Long-term unemployment has a more acute impact on these socio-economic issues than short-term unemployment. These socio-economic issues inhibit further job search creating a self-perpetuating cycle of unemployment (Eriksson and Gottfries, 2000).

Unemployment affects human capital through a loss of skills and experience (Möller, 1990; Frijters and van der Klaauw, 2006; Edin and Gustavsson, 2008). Long-term unemployment has serious implications for future labour market outcomes as duration dependence manifests. Future wages and earnings potential are also negatively affected by the duration of unemployment (Cooper, 2013). The duration of unemployment also affects employers’ perception of job seekers. Job seekers with longer unemployment durations receive lower rankings (from potential employers), which decreases likelihood of them receiving a job offer, and therefore decreases the probability that they will transition out of unemployment (Eriksson and Gottfries, 2000).

Economic theory and evidence suggest that reservation wages are an important determinant of the duration of unemployment (Jones, 1988; Cahuc and Zylberberg, 2004; Addison, Machado and Portugal, 2013; Eubanks and Wiczer, 2016). Reservation wages provide insight into what job seekers' expectations are with regard to wages, while a key element in understanding what drives people's behaviour is understanding what their expectations and aspirations are (Brown and Taylor, 2011). The reservation wage plays a central role in job search theory. It can be described as the lowest wage that will be accepted by an individual to exit unemployment (Mortensen, 1986; Brown and Taylor, 2011). Job search theory describes that the reservation wage will affect whether a transition out of unemployment will take place: if the reservation wage is greater than offered wages, the worker will continue searching for a job, and the unemployment spell will continue.

Reservation wages are linked to unemployment duration theoretically through job search theory; this linkage has been confirmed empirically in various studies (Bloemen and Stancanelli, 2001; Krueger and Mueller, 2014). Other studies (Algan et al., 2003; Détang-Dessendre and Gaigné, 2009; Uysal and Pohlmeier, 2011) have also established age and education as important variables impacting reservation wages, thereby influencing unemployment duration.

The contribution of the proposed study is to be one of the first since Kingdon and Knight (2004) to use national panel data for South Africa to study the effects of reservation wages (in addition to age, gender and educational attainment) on the duration of unemployment. To my knowledge, it is also one of only a few studies to use South African data to examine how reservation wages (in addition to age, gender and educational attainment) affect unemployment transitions.

1.3 Problem Statement

With one of the highest unemployment rates in the world, unemployment is a critical issue in South Africa. An ominous landscape is sketched by the long-term nature of unemployment and the concentration of unemployment among workers with a low educational attainment, women, and youths. Furthermore, long-term unemployment has serious implications for poverty, skills deterioration and other socio-economic issues which reinforces the unemployment state. According to basic job search theory, the duration of unemployment is affected by the reservation wage, which is affected by the net income received during unemployment, as well as the rate of arrival of job offers, amongst other things. Furthermore, personal characteristics, like age, education and gender, are often found to interact with the reservation wage to influence duration (Bloemen and Stancanelli, 2001; Nattrass and Walker, 2005).

Insight into the effect of reservation wages on transitions from unemployment and the duration of unemployment across age groups, levels of education and gender will be valuable to policymakers for direction.

1.4 Research aim and objectives

Persistently high unemployment rates are associated with high long term unemployment rates, which has immense negative socio-economic implications. Reservation wages are linked to unemployment duration theoretically through job search theory; this linkage has been confirmed empirically in various studies (Bloemen and Stancanelli, 2001; Krueger and Mueller, 2014). Other studies (Algan et al., 2003;

Détang-Dessendre and Gaigné, 2009; Uysal and Pohlmeier, 2011) have also established that age and education impact reservation wages and unemployment duration.

The aim of this study is to investigate if reservation wages influence unemployment transitions and the duration of unemployment in South Africa.

The main objectives of this study are to:

- Determine if reservation wages affect unemployment transitions.
- Determine if reservation wages affect unemployment duration.

The secondary objectives of this study are to:

- Determine if age, gender and the level of educational attainment affect unemployment transitions.
- Determine if age, gender and the level of educational attainment affect unemployment duration.
- Determine if reservation wages differ by age, gender and level of education.

1.5 Chapter outline

This section provides an overview of the remaining chapters of this study.

Chapter 2 is a survey of the literature. It begins by surveying the theoretical literature on unemployment transitions and unemployment duration, and then proceeds with a methodological review of previous studies, before surveying empirical studies that investigated the link between reservation wages and unemployment transitions and unemployment duration, in addition to the impact that age, level of education and gender have on unemployment transitions and duration. The chapter also discusses the results of South African studies on unemployment transitions, unemployment duration, and reservation wages.

Chapter 3 describes the methodology of the study; specifically, the research design, the data used, including a description of the study sample and study variables, as well as the research methods that were used to analyse unemployment transitions and unemployment duration.

Chapters 4 and 5 present the results of the study. Chapter 4 presents descriptive statistics about transitions from unemployment and the duration of unemployment, while Chapter 5 presents the results of unemployment transition regressions (binomial logit and probit, as well as multinomial logit and probit regressions), as well as the results of unemployment duration regressions (binomial logit and probit regressions).

Chapter 6 concludes with a summary of the key research findings and their relation to the research aim and objectives. Furthermore, it describes the limitations and contribution of the study, and identifies future research opportunities and some policy implications.

1.6 Conclusion

In this chapter, I elaborated on the background and motivation for the study, introduced the problem statement, outlined the research aim and objectives, and provided a chapter outline for the chapters that will follow.

Chapter 2: Literature review

2.1 Introduction

In this chapter I will summarise the theoretical, empirical and methodological literature on the link between reservation wages and the duration of unemployment. The empirical review includes the role that age, gender and the level of educational attainment play in transitions from unemployment and the duration of unemployment. Furthermore, this chapter also reviews evidence from South African studies about links between reservation wages and unemployment duration.

2.2 Theoretical background

Individual agents in the economy decide on their participation in the labour market. Individuals that decide to participate in the labour market have access to imperfect information about the location, type or wages of available jobs (Dinkelman, 2004). In the labour market, price (the wage) is not the only mechanism that matches the supplier (employee) with the demander (employer). Employees and employers must search for each other to overcome the labour market frictions imposed by the available imperfect labour market information.

Job search theory seeks to explain the search behaviour of individuals seeking employment (Sloane, Latreille and O'Leary, 2013). Many search models have been developed over time (e.g. those of Devine and Kiefer, 1991; Mortenson, 1986) to determine the optimal amount of search required before accepting a job or exiting the labour market (Dinkelman, 2004).

Devine and Kiefer (1991) and Cahuc and Zylberberg (2004) provide a useful description of the basic job search model. This section summarises the main ideas of the basic job search model, primarily relying on the work of Devine and Kiefer (1991).

The model rests on the following simple assumptions (Devine and Kiefer, 1991):

- the job seeker seeks to maximise the expected present value of future income (future income is discounted at rate *r* over an infinite horizon);
- the job seeker's income while unemployed is constant over the unemployment spell (it is denoted by *b* and is net of any search costs);
- job offers to the job seeker arrive according to a Poisson process (the arrival rate of job offers is denoted by δ);
- the job offer is a function of the wage rate *w* (if the job offer at *w* is accepted, *w* will be the constant wage received over the course of employment);
- independent draws from a known wage offer distribution with a cumulative distribution function *F(w)* and probability density of *f(w)* are made without recall;
- and if a job is accepted the job seeker will continue with the job forever.

The value of the search during unemployment, V^u, during time h is a function of the present value of the net unemployment income $\left(\frac{1}{1+rh}bh\right)$, the probability of receiving an offer (δh), multiplied by the expected present value of accepting the offer $\left(\frac{1}{1+rh}E_w[max\{V^e(w),V^u\}]\right)$; the probability of not receiving an offer $(1-\delta h)$, multiplied by the expected present value of continuing the search $\left(\frac{1}{1+rh}v^u\right)$; and the probability of receiving multiple offers $(o(h))$, multiplied by the value of following the optimal strategy in the case of multiple offers (K) (Devine and Kiefer, 1991; Cahuc and Zylberberg, 2004).

$$V^u = \frac{1}{1+rh}bh + \frac{\delta h}{1+rh}E_w[max\{V^e(w),V^u\}] + (1-\delta h)\frac{1}{1+rh}v^u + o(h)K$$

V^e, the expected present value of accepting the job offer, is equated to the present value of the future income received from that job offer's wage. Under the assumption that the wage will be constant and the job will be kept forever (Devine and Kiefer, 1991; Cahuc and Zylberberg, 2004):

$$V^e(w) = \frac{w}{r}$$

A job offer will be accepted if it offers a wage that is at least equal to the reservation wage, $w \geq w^r$, which describes the optimal search strategy. The reservation wage (w^r) can be described as the wage at which the job seeker will be indifferent between accepting the job offer and continuing the job search, in other words when the value of accepting a job offer (V^e) is equal to the value of continuing the job seach (V^u) (Devine and Kiefer, 1991; Cahuc and Zylberberg, 2004):

$$V^e(w) = \frac{w^r}{r} = V^u$$

By substituting equations 1 and 3:

$$\frac{w^r}{r} = \frac{1}{1+rh}bh + \frac{\delta h}{1+rh}E_w\left[max\left\{\frac{w}{r}, \frac{w^r}{r}\right\}\right] + (1-\delta h)\frac{1}{1+rh}\frac{w^r}{r} + u(h)$$

The optimal condition from the optimal search theory can then be defined by solving the equation to be rewritten in a form that facilitates its interpretation:

$$w^r = b + \frac{\delta}{r}\int_{w^r}^{\infty}(w - w^r)dF(w)$$

$$\therefore (w^r - b)r = (E_w[w|w \geq w^r] - w^r)[1 - F(w^r)]\delta$$

$(w^r - b)r$, shows the marginal cost of continuing a job search by rejecting an offer equal to the reservation wage. The right hand side of the equation is equal to the marginal gain from continuing the optimal search, which is a function of the expected future earnings from continuing the job search $((E_w[w|w \geq w^r] - w^r)[1 - F(w^r)]$)multiplied by the probability of receiving a job offer (δ).

The reservation wage is central to job search theory and reflects the individual's current circumstances, the characteristics of the labour market and the specific job offered. Changes in these factors will affect the reservation wage or the optimal stopping point in the search strategy. If b increases, the optimal stopping point would also likely increase as a result of the higher opportunity cost of accepting a job; this will lead to fewer job offers being accepted and could theoretically lead to longer unemployment spells (Dinkelman, 2004). If the probability of receiving a job offer increases, V^u and the reservation wage would increase, because the job seeker can afford to be particular about job offers. If search costs or the discount rate increases, it would lead to a lower reservation wage. However, where the reservation wage declines to a level below b, the job seeker will likely stop searching and exit the labour market.

The hazard rate and average duration of unemployment can be obtained using the reservation wage, which can be obtained using basic job search theory. The hazard rate provides the probability that the individual will transition to employment, on the condition that the current state is unemployment (Sloane, Latreille and O'Leary, 2013). The hazard rate *(τ)* is a product of the arrival rate of the job offers, δ, and the probability that the offer will be acceptable under the optimal search strategy, $\pi(w^r)$ (Devine and Kiefer, 1991):

$$\tau = \delta\pi(w^r)$$

In order to present a comprehensive model it is necessary to also account for those who decide to leave the labour force and transition into nonparticipation (Devine and

Kiefer, 1991). The basic theory of job search only makes provision for two states: employment and unemployment, while labour supply theory only differentiates between labour force participants and non-participants. These observations about job search and labour supply models call for the adoption of a hybrid model where three states are possible: unemployment (u), employment (e) and nonparticipation (n).

If the job seeker places a higher value on alternative activities than w^r and V^u, it will prompt the job seeker to leave the labour market and become a nonparticipant. The value of being a nonparticipant is indicated by (Dinkelman, 2004):

$$V^n = b$$

The labour market status of the individual, within the search framework, can be described as the relationship between the expected value of being employed, unemployed and nonparticipation. The expected values are dependent on the characteristics of the individual (Dinkelman, 2004) and the labour market environment which influences the reservation wage.

For the employed, the expected value of employment exceeds the expected value of the continued search, i.e. $V^e > V^u$. The unemployed have a higher expected value from continuing search than from being nonparticipants, or from being employed at the wages of job offers that have been rejected, i.e. $V^u > V^n$and $V^u > V^e$ (for rejected offers). Nonparticpants have higher expected values from being out of the labour force than from searching for employment, i.e. $V^n > V^u$. The value of nonparticipation is derived from alternative activities that would have to be foregone should nonparticipants search for employment (Dinkelman, 2004).

In the case of studying transitions from unemployment, the transition rate from state i to j, where $i = u, j = e, n$ (Devine and Kiefer, 1991) is:

$$\tau_{ij}(z) = \delta_i \pi_j(z)$$

The transition rate indicates that a job seeker can only transition to two possible states. It is obvious that a transition cannot take place to the same state as it would then not qualify as a transition as the previous state just continues. The hazard rate can then be written as (Devine and Kiefer, 1991):

$$\tau_i(z) = \sum_{j=e,n} \tau_{ij}(z)$$

This equation describes the transition rate out of state i (unemployment) and is defined as the sum of the transition rates j (employment and nonparticipation), which are defined as a function of the human capital *(z)* of the individual.

The average duration from unemployment, T_u, is inversely related to the hazard rate (Cahuc and Zylberberg, 2004):

$$T_u = \frac{1}{\delta\pi(w^r)}$$

This indicates that the duration of unemployment is inversely related to the arrival rate of job offers (δ) and the probability that the offer received is at least equal to the reservation wage ($\pi(w^r)$).

Duration dependence describes the relationship between the duration of the unemployment spell and the time already spent in unemployment. Positive duration dependence posits that the probability of a transition increases with the length of the unemployment spell. Negative duration dependence, on the other hand, contends that the probability of a transition decreases with the length on the unemployment spell (Cahuc and Zylberberg, 2004).

According to van den Berg and van Ours (1999), duration dependence should theoretically be negative: as the duration of an unemployment spell increases, there is loss of human capital that is exacerbated by the stigma the labour market attaches to long-term unemployment, which further reduces the opportunities available for the long-term unemployed. Individuals who have been long-term unemployed may also become discouraged if the costs of searching are too high, or if the probability of receiving a job offer becomes too low (Dinkelman, 2004). The value of unemployment for discouraged job seekers could be lower than their value of nonparticipation, but they could still derive a higher expected value from employment than from alternative activities (Dinkelman, 2004).

In the basic job search model, the probability of a transition is independent of time. It is also necessary that the duration dependence is non-monotonic: some values of time spent in unemployment may exhibit positive duration and others negative duration. For example, positive duration dependence could be exhibited until an unemployment duration of 3 months, thereafter negative duration manifests.

2.3 Methodological review

Within the theoretical framework of job search theory there are various econometric methods available to answer the questions: how do reservation wages affect transitions from unemployment and the duration of the unemployment spell?

The data that are available will provide guidance on the type of model and estimation method to be used. Hazard models are the preferred approach and can either estimate the length of the spell or the probability of the transition (Algan et al., 2003; Détang-Dessendre and Gaigné, 2009; Uysal and Pohlmeier, 2011). Discrete choice models provide a viable alternative where the available data does not meet the requirements for estimating duration models (Dinkelman, 2004; Krueger and Mueller, 2014). Linear models are also sometimes used (Bloemen and Stancanelli, 2001; Collier, 2005) to estimate the effect of explanatory variables on transitions and duration.

The simplest approach to modelling duration and transitions is to use linear models to condition explanatory variables on the duration or specifically a linear probability approach to estimate transitions. However, there are a few fundamental issues with using linear models for duration analysis: using a linear regression to estimate duration could result in a negative predicted variable which would not make practical sense for interpretation (Greene, 2012). In order to solve this problem, the dependent variable can be logged (Bloemen and Stancanelli, 2001; Collier, 2005):

$$\log t_i = x'_i\beta + \varepsilon_i$$

Where:

$t = duration$

$x = \begin{bmatrix} x_1 \\ \cdots \\ x_k \end{bmatrix}$, where $x_1, \dots, x_k$ are explanatory variables thought to affect duration.

Furthermore, linear models, specifically linear probability models, can be used to estimate transitions. Greene (2012), however, suggests that logit (and probit) models should rather be used as they allow explanatory variables to have non-linear effects on the dependent variable (Dinkelman, 2004, Krueger and Mueller, 2014). Although linear models provide a straightforward approach to conduct duration analysis, there are alternative econometric methods that provide a framework for more advanced analysis.

The preferred approach to modelling duration are hazard models, which estimate the likelihood of when an unemployed individual will exit unemployment as a function of time. There are two broad approaches that are used when estimating hazard models: a structural approach and a reduced-form approach. The structural approach requires complete data on duration and wages, and is estimated from a structural economic model (Algan et al., 2003, Collier, 2005). The reduced-from approach, on the other hand, does not require estimation of the parameters of a structural theoretical model -- it only requires data related to the duration of the job search (Algan et al., 2003, Collier, 2005). This is why the reduced-form approach is often the favoured approach (Cahuc and Zylberberg, 2004).

Algan et al. (2003) estimated reduced-form and structural models for the duration of unemployment. They first estimated a reduced-form model, and then confirmed their reduced-form results with the results from the estimation of the parameters of a theoretical search model, which is a structural model. Collier (2005), on the other hand, discusses all the assumptions that must hold in terms of job search theory, and concludes that if the assumptions can be accepted, a structural model is appropriate. But if they are not acceptable, job search theory provides a good theoretical basis and guidance to construct a reduced form model. Collier (2005) then estimates both structural and reduced-form models by using maximum likelihood estimation. According to the Hausman test conducted, the structural model was the appropriate model.

The hazard rate represents the probability of the exit rate from the state of unemployment. Various estimation techniques can be used to estimate hazard functions, with varying degrees of freedom and limitations. Mlatsheni and Leibbrandt (2015) estimated the degree of duration dependence of the unemployed youth in the

Cape Town using the panel data from the Cape Area Panel Survey from 2002 to 2006 with non-parametric, semi-parametric and parametric analysis.

Non-parametric estimation does not require any assumptions about the functional form of the hazard (Cleves et al., 2004). This approach does not make provision for controlling for the effect of explanatory variables on the hazard rate (Brick and Mlatsheni, 2008). Algan et al. (2003) and Mlatsheni and Leibbrandt (2015) used the Kaplan-Meier estimator, a pure empirical approach, in their non-parametric analysis.

Parametric estimation can address the limitation of the absence of explanatory variables from non-parametric estimation of hazard rates (Brick and Mlatsheni, 2008). However, it introduces other constraints. Parametric estimation requires the specification of a baseline hazard (Greene, 2012). The most common distributions used to specify the functional forms in duration models are the exponential-, Weibull- and log-logistic distributions (Cahuc and Zylberberg, 2004). Parametric models are also frequently used to model duration dependence (Mlatsheni and Leibbrandt, 2015). The table below provides a comparison of the hazard rate and duration dependence under the different distributions:

Table 2.1: Distributions used in duration models

Distribution	Hazard rate $\boldsymbol{\tau(t)}$	Duration dependence
Exponential	θ	No duration dependence
Weibull	$\theta a t^{a-1}$	Monotonic duration dependence
Log-logistic	$\frac{\theta a t^{a-1}}{1+\theta t^{a}}$	Non-monotonic duration dependence

Source: Cahuc and Zylberberg (2004)

The reliability of the results from parametric models depend on the correct model specification, while these models are also often criticised for their lack of robustness (Greene, 2012). Fortunately, an alternative, semi-parametric models, provides a solution. There are some advantages of using the semi-parametric approach over the parametric approach. The risk of misspecification is reduced, as the functional form of the baseline hazard does not need specification. It also makes provision for the inclusion of covariates and is suitable for discrete time series data. (Algan et al., 2003; Détang-Dessendre and Gaigné, 2009; Uysal and Pohlmeier, 2011).

Hazard models require specific data about the start and end date of an unemployment spell. The ideal data set for hazard models would be an administrative data set that consists of an individual's entire employment history. Such rich administrative data sets are seldomly available.

In the absence of an ideal data set, high frequency longitudinal data for a relatively long period of time can be useful. This is the approach followed by Krueger and Mueller (2014): they conducted their own survey in order to study the behaviour of reservation wages over a spell of unemployment using cross-sectional and longitudinal analysis. Survey data sets rely on the recall of the respondents. Data sets that are compiled with low frequency often suffer from inaccuracy about specific dates as respondents can't recall exact dates. Another issue is that the respondent could have been employed/unemployed more than once since the previous interview.

Longitudinal data with a lower frequency can be used to model transitions from unemployment and unemployment duration by means of discrete choice models (Cameron and Trivedi, 2005). Discrete choice models have dependent variables that indicate the probability of an outcome based on a set of covariates. Binary outcome models, such as logits and probits, are the most basic discrete choice models. Empirically, the predicted probabilities from the logit and probit models often differ very little (Cameron and Trivedi, 2005). The main difference between logit and probit models is that the error term of the logit is logistically distributed, while the error term of the probit model is normally distributed.

Logit and probit models allow researchers to model transitions to another state, for example from unemployment to employment. The outcome of the model will indicate whether a transition has taken place or not. Dinkelman (2004) estimated the impact of household variables on the search outcomes of jobseekers using a logit model. Logit and probit models cannot model transitions to employment and non-participation simultaneously – these models can only model one type of transition at a time, for example from unemployment to employment, or from unemployment to non-participation. To account for non-participation in the model, Dinkelman (2004) grouped the unemployed and not economically active participants together as jobless.

Multinomial models, specifically multinomial logit and multinomial probit models, allow for richer specifications, by allowing researchers to model more than two outcomes simultaneously. Therefore, with multinomial logit and probit models, transitions from unemployment to employment, and from unemployment to non-participation (as well as no transition) can be modelled simultaneously. The multinomial logit model was used by Poterba and Summers (1995) to model employment transitions and labour market withdrawals using data from the United States' Current Population Survey from 1976 onwards.

While hazard models should ideally be used to model unemployment duration, these models require detailed information about workers' labour market histories, so that accurate measures of the length of complete and incomplete unemployment spells can be obtained, as was discussed above. In the absence of complete labour market histories, researchers can estimate unemployment duration models by using data, often from household surveys, about the length of a person's current unemployment spell. This data is often captured in discrete time intervals, e.g. the person was unemployed for less than one month, for between one to six months, for between six months and a year, and for more than one year. Researchers can then use logit or probit models to model unemployment duration, for binary duration outcomes (e.g. an unemployed person is long-term unemployed or short-term unemployed) (Kingdon and Knight, 2004).

Alternatively, researchers could use ordered outcome models, such as ordered logit or probit models, to estimate duration models in which the duration of unemployment is recorded in more than two ordered intervals. Interval duration data is naturally ordered and therefore calls for the use of models that accommodate the ordinal ranking of the dependent variable. Han and Hausman (1990) based their flexible parametric proportional hazard model on the ordered probit model. This makes ordered logit and ordered probit models well-suited for duration analysis where only limited duration data is available. This approach was also used by Kingdon and Knight (2004) to study the effect of household income on unemployment duration in South Africa.

2.4 Empirical results

This section summarises the empirical results of research that studied the link between reservation wages and unemployment transitions and unemployment duration; the impact of age, education and gender on unemployment transitions and duration; and other relevant control variables present in the literature. The section concludes with the contribution of two prominent South African studies on the topic of reservation wages, transitions and unemployment duration.

2.4.1 Reservation wages, transitions and unemployment duration

Job search theory predicts that higher reservation wages are associated with a lower probability of a transition into employment and longer unemployment duration. But empirical studies on the relationship between reservation wages and unemployment transitions and durations have delivered conflicting results.

Addison, Centeno and Portugal (2004) found that the impact of reservation wages on the transition from unemployment to employment was negative and significant at a 5% level, based on European Community Household Panel data from 1994 to 1999, which includes data from 13 different European countries and estimated with a hazard model.

Krueger and Mueller (2014) also studied the relationship between reservation wages and subsequent employment, but what sets their study apart from other studies is a richer data set that they collected and used in their study. They collected their own high frequency longitudinal data set by interviewing unemployment benefit recipients from New Jersey (USA) weekly for up to 24 weeks. From this data set they obtained information about all the job offers that unemployed workers in their sample received over the sample period. Most other studies only have data on the acceptance or rejection of the job offers. They estimated a probit model with the dependent variable being the acceptance of a job offer. They found that the reservation wage had a negative relationship to the acceptance of a job offer, indicating that people with higher reservation wages were less likely to accept job offers. They further found that more than 50% of people who were offered jobs accepted job offers that offered wages below their reservation wage. The conclusion that they drew is that the level of the reservation wage does not necessarily affect the transition to employment.

Poterba and Summers (1995), estimated a multinomial logit model using the Current Population Survey data from the United States from May and June 1976 and found the reservation wage had a positive relationship for unemployment to employment transitions, and a negative relationship for transitions to inactivity. However, none of these relationships were statistically significant.

In line with Poterba and Summers (1995), Frijters and van der Klaauw (2006) studied the transitions from unemployment to non-participation based on annual panel data from Germany between 1989 and 1995. They argue that not accounting for the possibility of exit into non-participation could yield biased results. Frijters and van der Klaauw (2006), argued that people transition to non-participation when their reservation wages fall below the utility that they derive from non-participation. They also studied the relationship between the reservation wage and the duration of unemployment and found that the reservation wage decreases with the duration of unemployment. Collier (2005) studied whether the duration of unemployment is determined by personal characteristics, observed reservation wage and job search behaviour based on cross section microeconometric data collected in Kent County in the United Kingdom during October 1992. The results indicated a negative relationship between reservation wages and the duration of unemployment. The coefficient was significant at a 10% level of significance when estimated using Instrumental Variables.

The relationship between reservation wages and unemployment duration may also differ for different sub-sets of the sample. Holzer (1986) studied the effect of self-reported reservation wages on the unemployment duration of black and white American males aged between 16 and 21, using data from the 1979 NLS New Youth Cohort data. Holzer (1986) found that reservation wages were significant in explaining unemployment duration in young black males, but were insignificant for young white males. The relationship for young black males was found to be positive, while the relationship for young white males was found to be positive when estimated using weighted least squares (WLS), and negative when using ordinary least squares (OLS, Holzer, 1986).

Heath and Swann (1999) used data from the Survey of Employment and Unemployment patterns in Australia from 1995 to 1996 and they found that reservation wages have a significant impact on unemployment duration. Again, the direction of the effect depended on the estimation method that was used: a positive relationship was found when using OLS, while a negative relationship was found when using Instrumental Variables (IV).

The contradictory results in the existing literature suggests that further research into this relationship is needed. Care must also be taken when established results of the relationship between reservation wages and unemployment durations in certain countries or cohorts are extrapolated to other countries or cohorts, as different socio-economic circumstances may deliver different results (Nattrass and Walker, 2005). For example, in countries with low unemployment that offer adequate unemployment benefits, reservation wages can be expected to be higher, while the opposite can be expected in a country with a high unemployment rate and no unemployment benefits.

2.4.2 Age, education and gender

In addition to the effect of reservation wages on unemployment transitions and duration, many studies have also controlled for the effect that age, education and gender may have on unemployment transitions and duration.

Algan et al. (2003) and Détang-Dessendre and Gaigné (2009) found significant negative relationships between age and the duration of unemployment. Algan et al. (2003) estimated the hazard rate using a French panel data set for 1993 to 1996, with annual observations, and with wealth as the main variable of interest. Détang-Dessendre and Gaigné (2009) also used a French panel data set, but used observations from 1998 and 2003, with a constructed access index based on spatial distribution as the main variable of interest to estimate a hazard function. Uysal and Pohlmeier (2011) found a significant positive relationship between age and unemployment duration utilising a monthly German panel data set, covering the period from 1984 to 2007 to estimate a hazard model. Furthermore, the positive relationship was 50% higher for women than for men. The socio-economic context and underlying labour market dynamics of the subject countries most likely play a role in explaining these contradictory findings.

Several studies (Brick and Mlatsheni, 2008; Dinkelman, 2004; Mlatsheni and Leibbrandt, 2015) control for both age and its square. The motive for including the square of age is to allow for the presence of a non-linear relationship between age and transition rates. Brick and Mlatsheni (2008) studied the employment probabilities of the long-term unemployed by estimating the hazard rate using data from the 2000 Khayelitsha/Mitchell’s Plain (KMP) Survey. They found that both the age and age squared variables have a significant effect on the transition rate from unemployment. They found evidence of a positive, non-linear relationship: the transition rate increases with age, but only up to a certain age, after which it declines. Dinkelman (2004) estimated a logit model with data from the Kwa-Zulu Natal Income Dynamics Study (KIDS) between 1993 and 1998, and found that age had an odds ratio of more than one, implying a positive relationship between age and the transition rate (the odds of transition increase as age increases). Age squared had an odds ratio of less than one, implying a negative relationship (the odds of transition decreases as age squared increases). This was true for both men and women, and these odds ratios were significant at 1%. This confirms a quadratic relationship between age and unemployment transitions, as in Brick and Mlatsheni: the probability of transition increases with age, but only up to a certain age. This non-linear relationship was also found in Mlatsheni and Leibbrandt (2015), who estimated the hazard rate of youth using the CAPS data set, although the variables (age and age squared) were only significant at a 10% level.

Other studies (Kettunen, 1997; Riddell and Song, 2011; Uysal and Pohlmeier, 2011) found a non-linear relationship between educational attainment and unemployment duration. Uysal and Pohlmeier (2011) estimated a hazard model and found a significant, negative, convex relationship between educational attainment and unemployment duration. For women, the relationship is weaker for university graduates than for those who have vocational training, while the opposite was true for men.

Based on Finnish data from 1985 to 1986, Kettunen (1997) estimated a hazard model and found that the relationship between education and unemployment duration is U-shaped, reaching its turning point at 13-14 years of education. Essentially, the relationship turns positive at the highest education levels (master's degree, licentiate and doctor's degree).

Mlatsheni and Leibbrandt (2015) specifically focused on the effect of the difference between almost completing secondary schooling and completing secondary schooling on the probability to exit unemployment. They found that completing secondary schooling increases the hazard rate to exit unemployment by 61%, *ceteris paribus*. Brick and Mlatsheni (2008) found that the hazard rate for tertiary qualification holders is 76% higher than for those without a tertiary qualification. This result implies that those without a tertiary qualification can expect longer spells of unemployment.

In Dinkelman's (2004) study, the odds ratios for those with a matric qualification is 3.7 for women and 3.5 for men, indicating strong odds of transition to employment. These odds got much stronger for those with a post-matric qualification, increasing to 21.7 for women and 10.8 for men. Interestingly, Dinkelman's (2004) results show that the odds of transition for a particular level of education are much stronger for women than for men. For an education levels from grade 1 an up, the results indicate an odds ratio of more than one for women, but for men the odds ratio only increases above one for an education level above standard 6 (8 years of schooling).

Gender not only influences the underlying dynamics of how age or education affects unemployment transitions or duration, but it can also affect these variables directly. Brick and Mlatsheni (2008) and Mlatsheni and Leibbrandt (2015) found that unemployment transitions were higher among men than women: this effect was significant at a 1% level. Heath and Swan (1999) and Dinkelman (2004), also found that men have a higher probability of exiting unemployment, but this effect was insignificant. Dinkelman (2004) further showed that the impact of having pensioners in the household affects the employment transition odds of men and women differently: for women, having a male pensioner in the household decreases their odds ratio by 99%; having a female pensioner in the household increases their odds ratio by 430%. This indicates that gender can have a direct and indirect impact on unemployment transitions and duration.

2.4.3 Other control variables

Other control variables like wealth, spatial factors, race and household effects have also been shown to have significant effects on unemployment transitions and duration.

Both Bloemen and Stancanelli (2001) and Algan et al. (2003) studied the effect of wealth on labour market transitions. Although the two studies used different theoretical channels to link wealth and labour market transitions, both found that an increased level of wealth is associated with a lower probability of exit from unemployment. Bloemen and Stancanelli (2001) showed that a higher level of wealth increases the reservation wage, whilst Algan et al. (2003) directly estimate the effect of wealth on the transition rate. Both, Bloemen and Stancanelli (2001) and Algan et al. (2003) found a negative relationship between wealth and unemployment transitions.

Spatial factors also affect unemployment transitions, either through the reservation wage or directly. Détang-Dessendre and Gaigné (2009) estimated an access index that incorporates travel time, physical distance and the number of competitors there are for the same jobs. The results show that in large urban centres in France, access is an insignificant factor, while in rural areas and urban fringes, access increased the probability of a transition to employment. Dinkelman (2004) specifically tested whether being in an urban area affected the probability of unemployment transitions, the results (a odds ratio of less than one) indicate that being located in an urban area decreases the probability of transitioning out of unemployment. Dinkelman's (2004) findings are somewhat counterintuitive, as one would expect employment opportunities (and specifically the job offer arrival rate) to be greater in urban areas than in rural areas. However, there are also more job seekers in urban areas.

Andersson et al. (2014) found that increased spatial access result in a higher probability of a transition from unemployment, based on Longitudinal Employer-Household Dynamics (LEHD) data from the United States between 2000 and 2005. This data set combines administrative and survey data which provides information on more than 120 million people; however, the study only used a sub-sample of low-income job-seekers from specific metropolitan areas. Travel time was also found to be a significant factor for access to the labour market by Gobillon, Rupert and Wasmer (2014). They estimated the racial unemployment gap using a matching model based on cross sectional French data from 1999.

Many economic outcomes vary by race, and some studies have found that employment transition rates vary significantly by race, and that race also interacts with other factors that affect transition rates and unemployment. Gobillon, Rupert and Wasmer (2014) found that labour market factors like the number of available jobs, wages offered and the insurance benefits explained most of the unemployment rate gap between natives and African immigrants in France, although spatial factors like commuting distance that have a large degree of racial influence also have a significant effect. Holzer (1986) wanted to determine how race affects unemployment duration through the reservation wage, and found that while young black and white US males have similar reservation wages, the wage offers for young black males are lower, which results in a mismatch between the reservation wage and the wage offered which leads to longer unemployment spells. Mlatsheni and Leibbrandt (2015) considered how South African transition rates vary by race by including a race dummy, as well as by including the interaction of this race dummy with a secondary school completion dummy. The results indicated that Africans had much lower employment transition rates, while the interaction between the race and education dummies was not statistically significant, indicating that the effect of a completed secondary education on the transition rate did not differ for different race groups.

Based on job search theory, higher reservation wages are associated with lower transitions rates out of employment and longer unemployment duration. Hazard models are the preferred approach when studying unemployment transitions, but due to the unavailability of the required data (on the full labour market history of workers), logit/probit models can be used as an alternative. Multinomial logit/probit models are appropriate for transitions to more than two states.

Some studies delivered results that are in line with the theoretical model (Addison, Centeno and Portugal, 2004 and Kruger and Mueller, 2014), while other studies delivered results that contrast with the theoretical model (Poterba and Summers, 1995 and Frijters and van der Klaauw, 2006). The existing literature has established that unemployment transitions and duration vary by age, education and race. In addition, other control variables like wealth, location, race and household characteristics can have important multi-dimensional affects on unemployment transitions and duration.

2.4.4 South African studies about reservation wages and unemployment transitions and duration.

Next, I turn to studies that have used South African data to analyse the relationship between reservation wages and unemployment duration.

Kingdon and Knight (2004) mainly studied if unemployment in South Africa is voluntary, using data from the Southern African Labour and Development Research Unit (SALDRU) 1993 survey and the October Household Survey (OHS) from 1997. They tested whether persons remained unemployed because their reservation wages were too high. The results indicated that people did not remain unemployed due to excessively high reservation wages. However, Kingdon and Knight (2004) failed to draw a definitive conclusion, as they contend that the reservation wage question did not truly capture the willingness of non-working people to accept a job offer at the stated reservation wage.

Nattrass and Walker (2005) also asked if unemployment was high due to unrealistically high reservation wages, using data from Khayelitsha and Mitchell's Plain in Cape Town, collected in 2000-2001. They found that reservation wages were not unrealistically high and that they are in line with predicted wages for the unemployed (based on their observed characteristics).

Furthermore, Nattrass and Walker (2005) modelled the determinants of reservation wages, using OLS, and found a negative relationship between the duration of unemployment and reservation wages. They included the square of the duration of unemployment to determine if a quadratic relationship exists: the results indicated that the relationship between unemployment duration and reservation wages turned positive for those who had been unemployed for very long periods.

Zoch (2013) employed three South African data sets, National Income Dynamics Study (NIDS), Cape Area Panel Study (CAPS) and Labour Market Employment Study (LMES) to analyse reservation wages in South Africa. First by using Wave 1 (2008) of the NIDS data, Zoch (2013) estimated a regression model of the log of reservation wages and independent variables that could potentially influence the reservation wage. The results indicated, amongst other things, that gender, education and age have a significant influence on reservation wages. As expected, men had higher reservation wages than women, people with a higher level of education had higher reservation wages and older workers had higher reservation wages. Next, Zoch (2013) estimated a simultaneous equation model based on Wave 1 to 5 (2002-2009) of the CAPS data participants who have left schooling. The results indicated that reservation wages and unemployment duration was negatively correlated, but not statistically significant. The results further confirmed that education has a significant effect on reservation wages. Furthermore, the results also indicated that men had higher reservation wages and shorter unemployment duration relative to women.

Burger, Piraino and Zoch (2017) also found a negative relationship between the reservation wage and transitions from unemployment (statistically significant at conventional levels) based on the same data as Zoch (2013), estimated with a fixed-effects regression.

There is not an extensive literature studying the relationship between the unemployment transitions, duration of unemployment and reservation wages in the South African context. However, the results of the above-mentioned studies confirm a negative relationship between reservation wages and transitions from unemployment and the duration of unemployment. Two limitations associated with these studies are that the reliability of the reservation wage data captured by older survey instruments was questioned by one study (Kingdon and Knight, 2004), while all of the South African studies reviewed here only included people residing in the Cape Town Metropolitan Area.

2.5 Conclusion

In this chapter, I synthesised the theoretical background on which the study is based whereafter I proceeded to discuss the methodological framework for this type of research based on existing literature. Furthermore, I discussed the empirical results of existing literature on reservation wages, transitions and unemployment duration. The review of the empirical results included a discussion of the role of age, education and gender on reservation wages, transitions from unemployment and unemployment duration. I further elaborated on other control variables used in the existing literature and focussed on existing South African research that studied reservation wages, unemployment transitions and unemployment duration.

Chapter 3: Methodology

3.1 Introduction

In this chapter I will provide a brief background of the methodology preferred for transition and duration analysis, the limiations of the available data in South Africa and the alternative methods available based on the available data. I will proceed to present the research design and describe the data by elaborating on the study sample and the variables to be used in the study. I will further outline the methods for the descriptive statistics, unemployment transition regression analyses and the unemployment duration regression analyses.

3.2 Background

Duration analysis is the preferred method for determining the relationship between the reservation wage and the probability of a successful job search, while the preferred methods of duration analysis are hazard models (Algan et al., 2003; Détang-Dessendre and Gaigné, 2009; Uysal and Pohlmeier, 2011). However, hazard models require the complete labour market histories of workers, or at least the start and end dates of all jobs that workers may have had up to the date that data is collected. To the best of my knowledge, no nationally representative South African data set contains such complete labour market histories. However, the National Income Dynamic Study (NIDS), a nationally representative (at baseline) panel study, collects data about the labour market status of working-age people in each of its waves, allowing me to model transitions from unemployment between waves. Furthermore, NIDS also collects ordered, interval data about the length of time that unemployed persons have been without a job prior to the interview in each wave, allowing me to model unemployment duration in each wave.

While the type of data collected by NIDS does not allow for the estimation of hazard models for unemployment transitions and duration, this data does allow me to use discrete choice models, which offer a logical alternative to hazard models. Specifically, I used binomial logit and probit models, along with multinomial logit and probit models, to model unemployment transitions, while I use binomial logit and probit models to model unemployment duration.

3.3 Research design

The study is a non-experimental, quantitative empirical study. The quantitative analysis is based on secondary, publicly available, longitudinal data for South Africa.

Empirical studies are based on actual observations for the purposes of gaining knowledge. Empirical studies can be completed by means of quantitative or qualitative analysis. The aim and objectives of my research are best addressed by a quantitative approach. According to this approach, statistical techniques are employed to analyse numerical data. The study is non-experimental (specifically, observational), as it aims to determine non-causal associations between the dependent variable and independent variables, using observational (non-experimental) data. Therefore, secondary, longitudinal data obtained from household surveys is the most appropriate form of data to conduct the proposed study.

3.4 Data

The study makes use of secondary household survey data from the National Income Dynamics Study (NIDS), which is the first and only nationally representative South African panel study. It includes over 28 000 individuals and 7 300 households (Chinhema et al., 2016). NIDS collects data at the individual – for adults and children separately -- and household level. For adults, NIDS collects data about topics such as demographics, labour market participation, income from non-employment sources, health and education; for households, NIDS collects data about topics such as household location, household spending, mortality and living standards.

NIDS is conducted by the South African Labour and Development Research Unit (SALDRU), which is hosted by the Department of Economics at the University Cape Town (Chinhema et al., 2016). The first data was collected in 2008, with subsequent data collected in 2010, 2012, 2014/2015 and 2017. At the time that I obtained NIDS data for my study, five waves of NIDS data were collected and made publicly available. This study uses data from the adult and household questionnaires, from waves 3 and 4. Two wave analysis is commonly used and even preferred for studying transitions, even if multiple waves are available (Johnson, 2005). I have identified wave 3 and wave 4 as the appropriate waves. The data for wave 3 was collected from April to December 2012: this time period corresponds to the end of the last upward phase of the SA business cycle (SARB, 2021). During this period, 32 633 residents of 8 040 households were interviewed. The data for wave 4 was collected from October 2014 to August 2015: this time period corresponds to the beginning of the last downward phase of the SA business cycle, which was still ongoing at the time of writing (SARB, 2021). Overall, 37 396 people were interviewed, of which 25 268 were continuing sample members (CSMs), who are those who were part of the study during wave 1, while 12 128 were temporary sample members (TSMs), who are those who were not part of the study during wave 1. NIDS tracks the CSMs, but not the TSMs (Chinhema et al., 2016).

Panel data allows for the repeated observation of a set of variables or characteristics of the same subjects over multiple time periods. Therefore, panel data allows researchers to conduct analysis of the behaviour of subjects over time (Deaton, 1997): in this case, how a variable like the reservation wage affects unemployment transitions and unemployment duration. With panel data, it is also possible to allow the reservation wage in wave 3 to affect the unemployment transition that takes place between waves 3 and 4. Another advantage of panel data is that unobserved heterogeneity can be controlled for (Deaton, 1997). Two major disadvantages of household survey panel data are measurement error and attrition.

Measurement error is a common feature of household surveys (Deaton, 1997). Deaton (1997) suggests that when measurement errors are independent over time, instrumental variables can be used to construct consistent estimators by comparing difference- and within-estimators obtained from several periods of panel data. He further suggests that when measurement errors are not independent over time, parameters from regressions over alternative period differences cannot be compared.

Another common limitation of household survey panel data is attrition, which imparts selection bias (Alderman et al., 2001). NIDS publishes the attrition rates for each wave by comparing CSM responses in a particular wave to the CSM response rate in the preceding wave. The total attrition rate for wave 4 was 13.75% (NIDS, 2018). If the attrition is random, it will not pose a problem for the analysis. The underlying fundamentals of the survey, tracking core persons (CSMs), contributes to the minimisation of attrition (Dinkelman, 2004). However, attrition might be problematic if one group has a higher attrition rate than another group: for example, if the unemployed have higher attrition rates than the employed. One way to detect if attrition bias might be present is to compare the observable attributes of those who have left the study with those who have remained in the study. If attrition bias is present, methods like inverse probability weighting (IPW) may be used to correct for this bias (Woolridge, 2002). The data analysed in Appendix 1 show that there may be some differences between those that attrited between waves 3 and 4, and those that remained in both waves. However, these attrition logits and probits fit the data poorly, making the use of IPW inappropriate (also see Booysen and Geldenhuys, 2016).

'One-shot' questions capturing self-reported data about reservation wages, such as those used in NIDS, might be measured with error. Specifically, in the NIDS questionnaires, people who were not working at the time of the interview were asked: "What is the absolute lowest take-home wage that you would accept for any permanent, full-time work (per month)?" The data captured by this question were taken to be the reservation wages of non-working people. Two types of problems have been noted in other studies about how these types of questions might lead to mis-measurement of the reservation wage: first, Kingdon and Knight (2004) noted that respondents may report what they regard as a fair wage, given their personal characteristics, rather than their true reservation wage. However, the NIDS wave 3 and wave 4 adult questionnaires followed the 'lowest take-home wage' question with a question about what wage people regarded as a fair wage, given their personal characteristics. Given that NIDS separately asks about reservation wages and fair wages, people should be less confused about whether they should state their reservation wages or what they regard as fair wages, probably removing one source of measurement error for the reservation wage.

A second, and more fundamental, source of measurement error associated with 'one-shot' self-reported reservation wages was noted by Burger, Piraino and Zoch (2017). They argue that these type of self-reported reservation wages may suffer from over-estimation and response noise. Krueger and Mueller (2014) also note problems with self-reported reservation wages: specifically, they found that, relative to a calibrated search model, reservation wages started out too high, and declined too slowly over unemployment spells, indicating that the unemployed may misjudge their prospects or anchor their reservation wages to the wages that they received in their previous jobs.

However, Krueger and Mueller (2014) still found that self-reported reservation wages contained useful information. In particular, they found that self-reported reservation wages did help to explain job acceptance, even though a large proportion of unemployed people accepted jobs that had wages that were lower than their reservation wages. Krueger and Mueller (2014) stated that the non-wage characteristics of accepted job offers, such as commuting time or distance, and fringe benefits, are also important factors in decisions to accept or reject job offers. These non-wage characteristics might not be strongly correlated with offered wages, leading to acceptance of jobs in which offered wages are less than reservation wages. Therefore, while the limitations associated with self-reported reservation wages should be born in mind when interpreting results, the fact that they helped explain job acceptance could mean that they contain potentially useful information about unemployment transitions and duration.

3.4.1 Study sample

Since the aim and objectives of my study involve the analysis of unemployment transitions between waves 3 and 4 of NIDS, as well as the analysis of unemployment duration in waves 3 and 4, I limited my sample to people who were CSMs and who were searching and non-searching unemployed in wave 3.

In wave 3, there were 2 374 searching unemployed people of which 962 (40%) were men and 1412 (605) were women. Almost 90% (2100) of the searching unemployed were African and 10% (249) were Coloured, while Whites and

Indians/Asians accounted only about 1% of the searching unemployed. Similar proportions were present in the non-searching unemployed sample.

There were 671 observations for unemployment duration in wave 3 of which 237 (35%) were men and 434 (65%) were women; 68% of the sample were African, 27% were Coloured, 4% were White and less than 1% were Indian/Asian. There were 773 observations for unemployment duration in wave 4, of which 291 (38%) were men and 482 (62%) were women. Similar proportions of race were present in wave 4 than in wave 3.

3.4.2 Study variables

The main variables of interest are transitions from unemployment, the duration of unemployment and the reservation wage.

To analyse unemployment transitions, I constructed binomial (u2e and u2n) and multinomial (uen) categorical transition variables, which capture whether someone who was unemployed in wave 3 was unemployed, employed, or economically inactive in wave 4. Table 3.1 below shows these categorical transition variables.

Table 3.1 Transition variables

Short variable name	Transition captured	Values
u2e	Unemployment to employment	0 = No transition, 1 = Employment
u2n	Unemployment to inactivity	0 = No transition, 1 = Inactivity
uen	Unemployment to employment or inactivity	0 = No transition, 1 = Employment, 2 = Inactivity

The variables in Table 3.1 above were created for both the searching and non-searching unemployed. The searching unemployed only includes those who were unemployed according to the strict definition of unemployment, i.e. those who were not employed in the seven days before the interview, who were willing and able to work, and who took active steps to search for employment or to start some form of self-employment activity in the four weeks preceding the interview; the non-searching unemployed also were not employed or self-employed, and willing and able to begin work, but they did not take active steps to find work or begin self-employment. The non-searching unemployed therefore includes those who had become discouraged job seekers (Stats SA, 2021).

To analyse unemployment duration, I constructed a binomial unemployment duration variable using data from a question in the NIDS questionnaire that captured data about how long it has been since a person, who was not employed at the time of the interview, has worked. This data were originally captured using seven ordered intervals: less than 3 months; 3 to 6 months; 6 to 9 months; 9 to 12 months; 1 to 3 years; 3 to 5 years; more than 5 years. Because most of these original intervals contained few observations, I combined the categories of the first four intervals (time since last worked is 0-12 months) into one category, while I combined the last 3 intervals (time since last worked is at least one year) into another category. The resulting unemployment duration variable is equal to one if someone last worked at least 1 year ago (i.e. that person was long-term unemployed), while it is equal to zero if someone worked less than one year ago (i.e. that person was short-term unemployed). This distinction between long-term and short-term unemployment accords with the distinction used by Statistics South Africa (Stats SA) in its Quarterly Labour Force Surveys (Stats SA, 2021).

While I used the panel structure of NIDS to create the unemployment transition variables, I created separate unemployment duration dummies for waves 3 and 4, which means that I analysed unemployment duration cross-sectionally in wave 3 and

4. I did this because, as explained previously, NIDS does not collect complete labour market histories, while the unemployment duration data in NIDS is captured in intervals with differing lengths, thereby making it extremely difficult to construct accurate unemployment spells over two waves, as opposed to simply analysing duration data separately in each wave.

In the NIDS data, the variable 'noemrw' captures data about the absolute lowest wage that a person, who is not currently employed, would accept for permanent, full-time work. I used the data collected by this question as the reservation wage of unemployed people.

In addition to these three variables, I also used NIDS data about age, education and gender, as well as further individual-level data, such as race and marital status, and household-level data such as per capita income, household location, household grant receipt and household size. Table 3.2 below provides a brief description of the individual- and household-level variables that I used in this study, in addition to unemployment transitions, unemployment duration and the reservation wage described above.

Table 3.2 Additional variables used in the study

Variable **(name used in analysis in parentheses)**	**Description**
Age	In the descriptive statistics, I used the following age categories: Young = 15 to 24 years, Prime-aged = 25 to 50 years, Pension-aged = 51 to 60 years, Old = Older than 60 years In the regressions, I used a continuous variable indicating the age of the respondent.
Education	No schooling = 0, Incomplete primary = 1, Complete primary = 2, Incomplete secondary = 3, Complete secondary = 4, Post-secondary education = 5
Gender	Female=0, Male=1

Race	White = 0, Asian/Indian = 1, African = 2, Coloured = 3
Marital status	Married/Living with a partner = 0, Other=1
Per capita income	Household income divided by the number of household residents
Province	Eastern Cape = 0, Free State = 1, Gauteng = 2, KwaZulu-Natal = 3, Limpopo = 4, Mpumalanga = 5, North West = 6, Northern Cape = 7, Western Cape =8
Urban/Rural	Rural=0, Urban=1
A member if the household received a government grant (hhGrant)	Not received=0, Received=1
A member if the household received a state pension (hhpension)	Not received=0, Received=1
A member if the household received a child support grant (hhChild)	Not received=0, Received=1
Household size (hhsize)	Number of residents in the household

These individual and household characteristics were used as additional control variables in the models described in sections 3.5.2 and 3.5.3 below.

3.5 Methods

In this section, I discuss the methods that I used to analyse the data to help me achieve my research aim and objectives. Specifically, I discuss the descriptive statistics and regression models that I used to analyse unemployment transitions and unemployment duration.

3.5.1 Descriptive statistics

Descriptive statistics provide information about the basic features of the data set and normally include graphic and tabular representations of these basic features. These statistics can also be used to uncover relationships that may exist between variables.

For the transition data, I compiled transition matrices and plotted histograms for the distribution of unemployment transitions, conditioned on age, level of education and gender, as well as histograms for the distribution of transitions conditioned on interactions of the following pairs of variables: (i) age and gender, (ii) age and level of education, and (iii) gender and level of education. I also conducted chi-squared tests of statistical independence to determine if the unemployment transitions are independent of age, level of education and gender. Furthermore, I also conducted various two-sample t-tests to determine if mean reservation wages differ significantly between: (i) those that remained unemployed and those that transitioned to employment, and (ii) those that remained unemployed and those who transitioned to inactivity.

For the duration data, I plotted histograms of the distribution of the rate of long-term unemployment conditioned on age, level of education and gender, while I also plotted histograms of the distribution of the rate of long-term unemployment conditioned on interactions of the following pairs of variables: (i) age and gender, (ii) age and level of education, and (iii) gender and level of education. I also performed chi-squared tests of statistical independence to determine if the duration of unemployment is independent of age, level of education and gender. Furthermore, I also conducted various two-sample t-tests to determine if mean reservation wages differ significantly between long-term and short-term unemployed.

3.5.2 Regression analysis: Modelling unemployment transitions

As discussed in the data sub-section above, the lack of complete employment histories in NIDS meant that I had to use discrete choice models, rather than hazard models, to explain and model unemployment transitions and duration. To model unemployment transitions, I estimated binomial logit and probit regressions, as well as multinomial logit and probit regressions. While studies modelling binomial transitions with binomial models seem to prefer using the logit model (e.g. Poterba and Summers, 1995; Dinkelman, 2004), empirically, there should only be slight differences between the estimates of these models.

The first set of unemployment transition models that I estimated are binary transition logit and probit models. I estimated separate models for transitions from unemployment to employment (along the lines of Dinkelman, 2004), and for transitions from unemployment to inactivity. The reservation wage is the main explanatory variable of interest, while age, level of education and gender are of secondary importance. Additional individual- and household-level controls were described in Table 3.2. To try and avoid possible simultaneity between the transition variables and some of the explanatory variables – particularly between transitions and the reservation wage -- transitions from unemployment were modelled as functions of one-period lags of all of the explanatory variables, i.e. the values that these variables took on in wave 3.

The unemployment to employment ($u2e$) transition is modelled as:

$$\Pr(u2e = 1|Reservation\,wage_{-1}, x'_{-1}) = \alpha_i + \beta_1(Reservation\,wage_{-1}) + \beta_2\left(x'_{-1,i}\right) + \varepsilon_i \quad 3.1$$

While the unemployment to inactivity ($u2n$) transition is modelled as:

$$\Pr(u2n = 1|Reservation\,wage_{-1}, x'_{-1}) = \alpha_i + \beta_1(Reservation\,wage_{-1}) + \beta_2\left(x'_{-1,i}\right) + \varepsilon_i \quad 3.2$$

Recall that $u2e = 1$ if a wave 3 unemployed person was employed in wave 4, and is zero if a wave 3 unemployed person was also unemployed in wave 4; $u2n = 1$ if a wave 3 unemployed person was economically inactive in wave 4, and is zero if a wave 3 unemployed person was also unemployed in wave 4. Furthermore, x is a vector containing age, highest level of education completed, gender, race, marital status, household size, per capita household income, whether the household is located in an urban or rural area, household grant receipt and provincial dummies. Also in each model, α_i is a constant, the βs are slope coefficients, and ε_i is an error term.

I estimated eight versions of equations (3.1) and (3.2): first, each model was estimated separately for the searching and non-searching unemployed. Each model was also estimated separately using logit or probit. And lastly, two versions of equations (3.1) and (3.2) were estimated that accounted for two ways in which household grant receipt may affect transitions. In the first versions, I included $hhGrant$, which captures whether an initially unemployed person resided in a household in which any grant income (from any type of government grant) was received. In the second versions I included $hhPension$ and $hhChildGrant$, which capture whether an initially unemployed person resided in a household that received grant income from an old persons grant (the state old-age pension) or a child support grant. These two grants are respectively the largest in terms of rand value and the largest in terms of number of beneficiaries. This was done to allow for the possibility that different grants could impact transitions differently. Thereafter, all of the models were estimated by including long-term unemployment as an additional explanatory variable. To facilitate the interpretation of the coefficient estimates, I obtained predicted probabilities for all of these binomial transition models, and plotted how these predicted probabilities varied with variation in the explanatory variables.

After the estimation of separate transition models for transitions to employment and transitions to inactivity, I then followed the example of Poterba and Summers (1995) and used multinomial transition models to model transitions to employment or inactivity (uen) simultaneously. These multinomial transition models had similar specifications to the binomial transition models (3.1) and (3.2) described above. The uen transitions were modelled jointly, using:

$$P(uen = j) = F_j(Reservation\ wage_{-1}, \beta_1, x_{-1}, \beta_2) \qquad 3.3$$

Where $j = 0, 1, 2$; $j = 0$ if wave 3 unemployed were also unemployed in wave 4; $j = 1$ if wave 3 unemployed were employed in wave 4; $j = 2$ if wave 3 unemployed were economically inactive in wave 4. Furthermore, F_j represents different multinomial models, such as the multinomial logit and multinomial probit models (Cameron and Trivedi, 2005), x denotes a vector of individual- and household-level control variables (which was first described in Table 3.2 above, and are the same individual- and household-level variables included in the binomial transition models), and the βs are slope coefficients. To avoid possible simultaneity, lagged values of the explanatory variables, including the reservation wage, were used to model transitions.

The specification and estimation of the multinomial transition model proceeded in a similar fashion to the specification and estimation of the binomial transition models. I estimated eight versions of equation 3.3: I estimated this multinomial transition model separately for the searching and non-searching unemployed, while I also used two ways to account for household grant receipt. The first way in which I accounted for household grant receipt was to control for whether a household received grant income from any type of government grant ($hhGrant$), while the second way was to control for the inclusion of household receipt of two specific government grants: the older-persons grant ($hhPension$) and the child support grant ($hhChildGrant$). Furthermore, each multinomial transition model was estimated using the multinomial logit and multinomial probit regression. Thereafter, I estimated all the models to include long-term unemployment as an additional explanatory variable.

As was the case following the estimation of the binomial unemployment transition models, I obtained predicted probabilities following the estimation of the multinomial transition models, and plotted how these predicted probabilities varied with variation in the explanatory variables, to facilitate the interpretation of my estimates.

3.5.3 Regression analysis: modelling the duration of unemployment

Due to a lack of complete employment histories in NIDS, I had to use discrete choice models, instead of hazard functions, to model unemployment duration. Specifically, I used binomial logit and probit models to model unemployment duration. In these binomial logit and probit unemployment duration models, the dependent variable, $lt\_unemployment$, equals one if an unemployed person last worked at least 12 months ago, and equals zero if an unemployed person last worked less than 12 months ago. As discussed in section 3.2 above, I estimated the duration models separately for wave 3 and wave 4 of the NIDS data. The main explanatory variable of interest was again the reservation wage, while I used the same individual- and household-level controls that I used to model unemployment transitions to model long-term unemployment. Long-term unemployment was then modelled using:

$$\Pr(lt\_unemployment = 1|Reservation\,wage, x') = \alpha_i + \beta_1(Reservation\,wage) + \beta_2(x_i') + \varepsilon_i \quad 3.4$$

As in the transition models described above, α_i is a constant, the βs are slope coefficients, x is a vector of individual and household controls (the same set of controls that were included in equations 3.1-3.3), and ε_i is an error term.

Simultaneity issues may arise with the inclusion of the contemporaneous reservation wage as explanatory variable for long-term unemployment, because the duration of unemployment and reservation wages may be jointly determined -- duration affects reservation wages and reservation wages affect duration (for example, see Nattrass and Walker, 2005). The duration models were estimated with (Table 5.3a) and without (Table A2) the reservation wage to determine if the estimates differ significantly if the reservation wage is excluded, with significant differences between the estimates indicating possible endogeneity.

3.6 Conclusion

In this chapter I provided some background information on the preferred method for this type of study, the restrictions of the available South African data, as well as alternative methods that can be used with the available data. I presented the research design and discussed the data by identifying the study sample and variables. Furthermore, I identified the methods that I used to analyse the data by elaborating on the descriptive statistics and regression models that I estimated for unemployment transitions and unemployment duration.

Chapter 4: Descriptive Statistics

4.1 Introduction

In this chapter I present the descriptive statistics – transition matrices, frequencies, proportions, chi-squared independence tests, means and t-tests for differences between means – for unemployment transitions, duration of unemployment and reservation wages.

4.2 Unemployment transitions and reservation wages

In Table 4.1 a, the transition matrix below shows the number of individuals who are searching- and non-searching unemployed in wave 3 (rows) and their labour market status - remain unemployed, become employed or become inactive - in wave 4 (columns).

Table 4.1 a Transition matrix - Transitions from searching and non-searching unemployment

Wave 3	Wave 4			
	Unemployed	**Employed**	**Inactive**	**Total**
Searching unemployed	596 (25.1)	998 (42.0)	780 (32.9)	2374 (100.0)
Non-searching unemployed	807 (27.5)	1168 (39.8)	963 (32.8)	2938 (100.0)

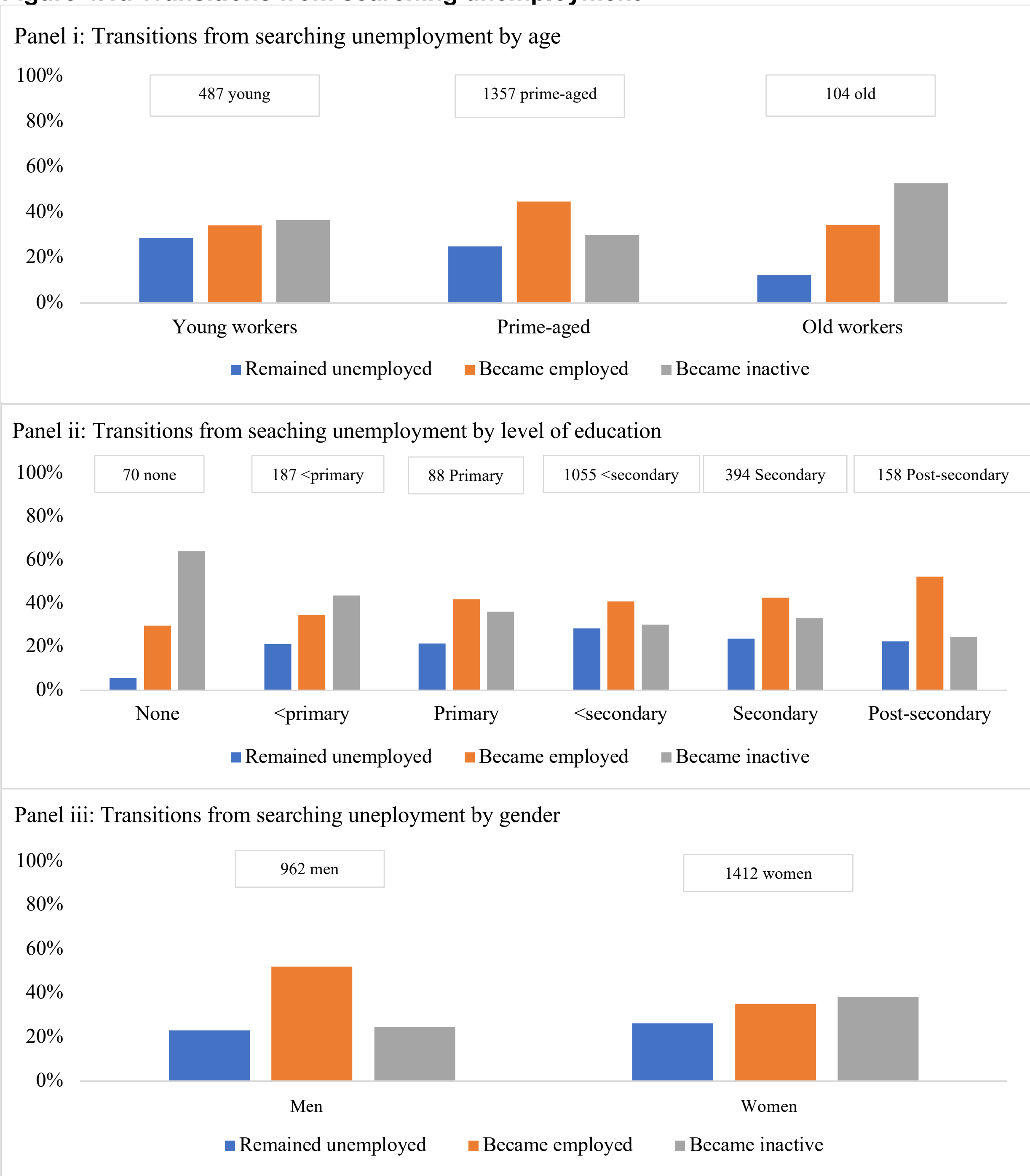
Source: Author's calculations using NIDS (W3 and W4) data. Notes: Values in parentheses are percentages.

The proportions for each labour market state attained in wave 4 are very similar for the searching and non-searching unemployed, with the largest difference (2.4 percentage points) being between the proportions of searching and non-searching unemployed remaining unemployed in wave 4.

About 40% of the searching and non-searching unemployed in wave 3 transition to employment in wave 4, while just more than a quarter remained unemployed in wave 4.

This pattern, that a plurality of those who are unemployed in wave 3 transition to employment in wave 4, (shown in Table 4.1 **a**) is not repeated when stratifying (conditioning) the unemployment transitions by age group, level of education and gender. The three panels of Figure 4.1a below shows transitions from searching unemployment by age, level of education and gender.

Figure 4.1a Transitions from searching unemployment



Source: Author's own calculations using NIDS (W3 and W4) data. Notes: Numbers above bars are the number of observations for those groups. Young workers are 15 to 25 years old, prime-aged workers are between 25 and 50 years old, and old workers are between 51 and 60 years old. There are only 10 searching unemployed workers above 60 years old (pension-aged), they have been excluded from the figure to avoid distortion of the figure. Of the 10 pension-aged workers, 20% (2) transitioned to employment and 80% (8) transitioned to inactivity.

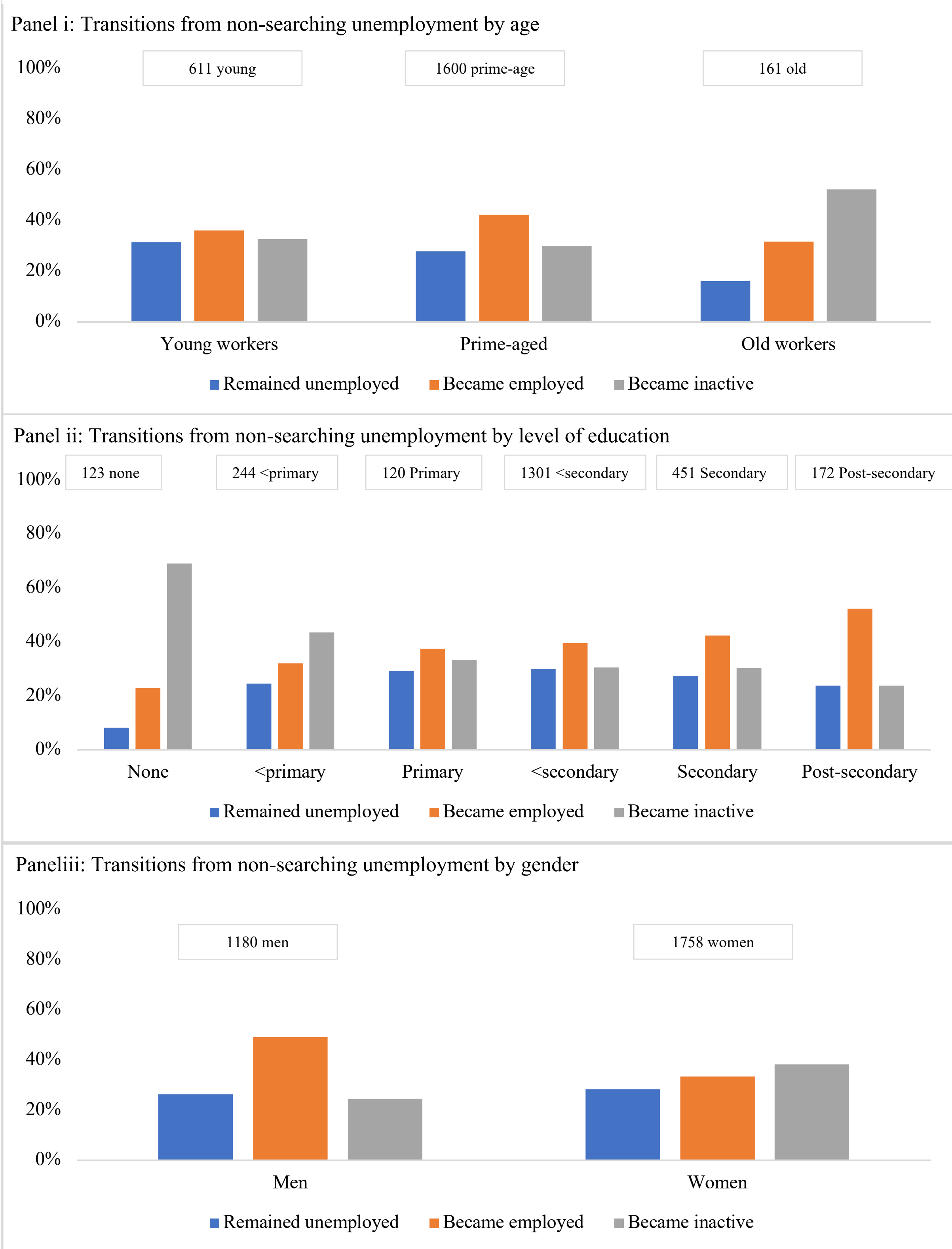
Most searching unemployed workers transition to employment or inactivity in wave 4. Young and old workers were more likely to transition to inactivity than to employment -- young workers are only slightly more likely to transition to inactivity, while old workers are much more likely to do so. Prime-aged workers, on the other hand, are much more likely to transition to employment than to inactivity.

Irrespective of their level of educational attainment, the searching unemployed in wave 3 are more likely to transition to employment or inactivity. Those whose level of attainment was less than a completed primary education are more likely to transition to inactivity than to employment, while those whose level of attainment was at least a completed primary education are more likely to transition to employment than to inactivity. This is especially true for those who at least completed secondary education.

Most searching unemployed men and women transition to employment or inactivity in wave 4. But men are more likely to transition to employment than to inactivity, while women are more likely to transition to inactivity.

Figure 4.1b below shows transitions from non-searching unemployment, stratified by age, level of education and gender.

Figure 4.1b Transitions from non-searching unemployment

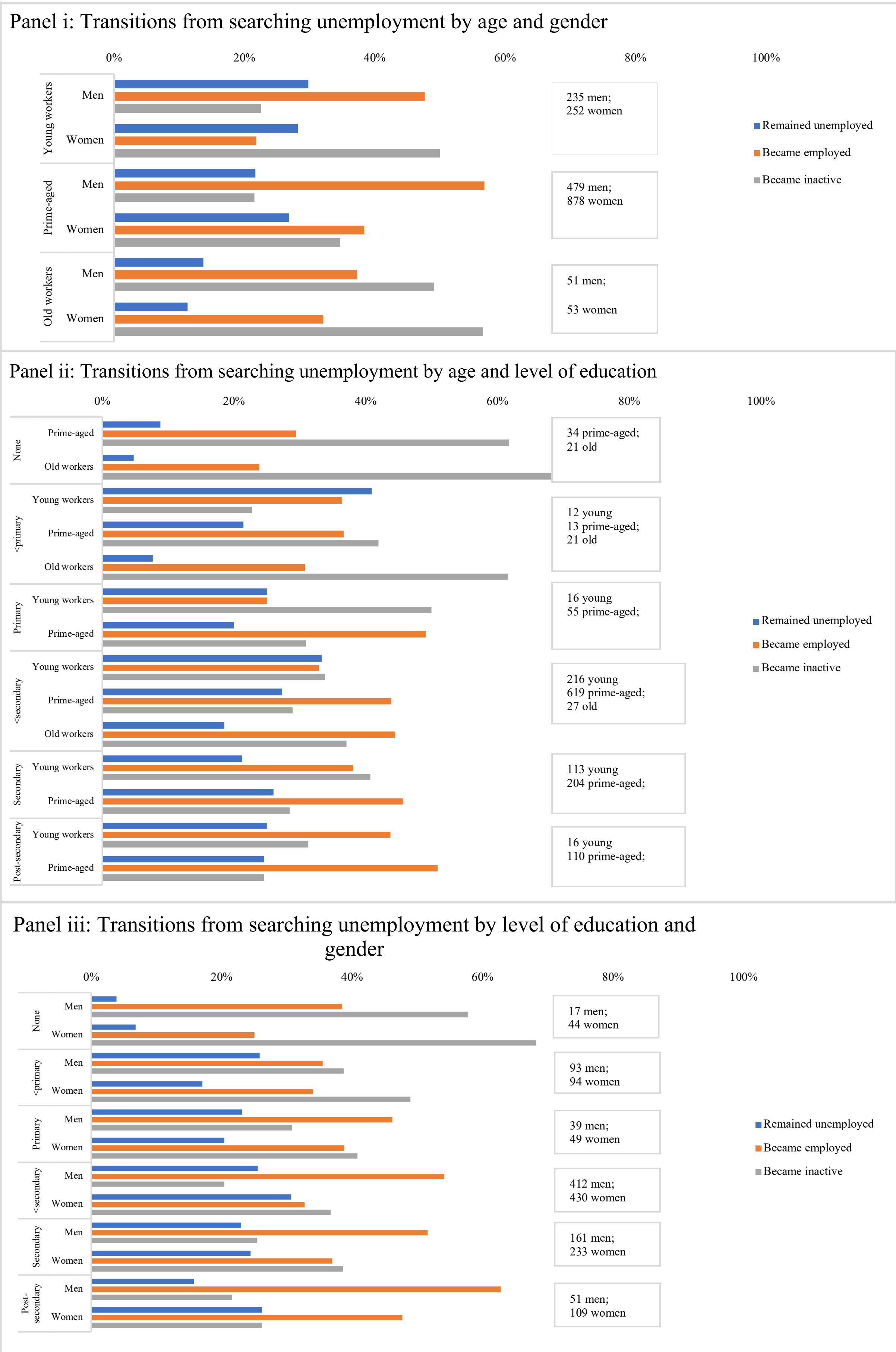


Source: Author's own calculations using NIDS (W3 and W4) data. Notes: Numbers above bars are the number of observations for those groups. Young workers are between 15 and 25 years old, prime-aged workers are between 25 and 50 years old, and old workers are between 51 and 60 years old. There are only 50 non-searching unemployed workers above 60 years old (pension-aged), and they have been excluded from the figure to avoid distortion of the figure. Of the 50 pension-aged workers, 12% (6) transitioned to employment and 88% (44) transitioned to inactivity.

The unemployment transition patterns observed in Figure 4.1b are similar to those observed in Figure 4.1a for the searching unemloyed: irrespective of age, level of education or gender, the non-searching unemployed are more likely to transtion to employment or inactivity than to remain non-searching unemployed in wave 4. Young and old workers are more likely to transition to inactivity than to employment, while prime-aged workers are more likely to transition to employment. Those with less than a completed primary education are more likely to transtion to inactivity, while those with at least a completed primary education are more likely to transition to employment. And non-searching unemployed men are more likely to transition to employment, while non-searching unemployed women are more likely to transition to inactivity.

To further determine how transition varies with age, gender and level of educational attainment, Figure 4.1c below shows transitions from searching unemployment, conditioned on the levels of the following pairs of variables: (i) age and gender; (ii) age and level of education; (iii) gender and level of education.

Figure 4.1c Transitions from searching unemployment (by age and gender, by level of education and age, and by level of education and gender)



Source: Author’s own calculations using NIDS (W3 and W4) data. Notes: Numbers next to bars are the number of observations for those groups. Young workers are 15 to 25 years old, prime-aged workers are between 25 and 50 years old and old workers are between 51 and 60 years old. Categories with very few observations have been excluded from the figure to avoid distortion. Pension-aged workers (above 60 years old) are excluded on Panel i - Of the 4 observations for men who were searching unemployed in wave 3, 1 (25%) became employed and 3 (75%) became inactive in wave 4. There are 6 pension-aged women who were searching unemployed in wave 3, of which 1 (16,7%) became employed and 5 (83,3%) became inactive in wave 4.

Almost half of young men are likely to transition to employment, while they are more likely to remain unemployed than to transition to inactivity; about half of young women transition to inactivity, while they are more likely to remain unemployed than to transition to employment. Just like young men, prime-aged men are most likely to transition to employment and least likely to transition to inactivity; prime-aged women, unlike young women, are most likely to transition to employment and least likely to remain unemployed. Old working men and women are most likely to transition to inactivity, and least likely to remain unemployed.

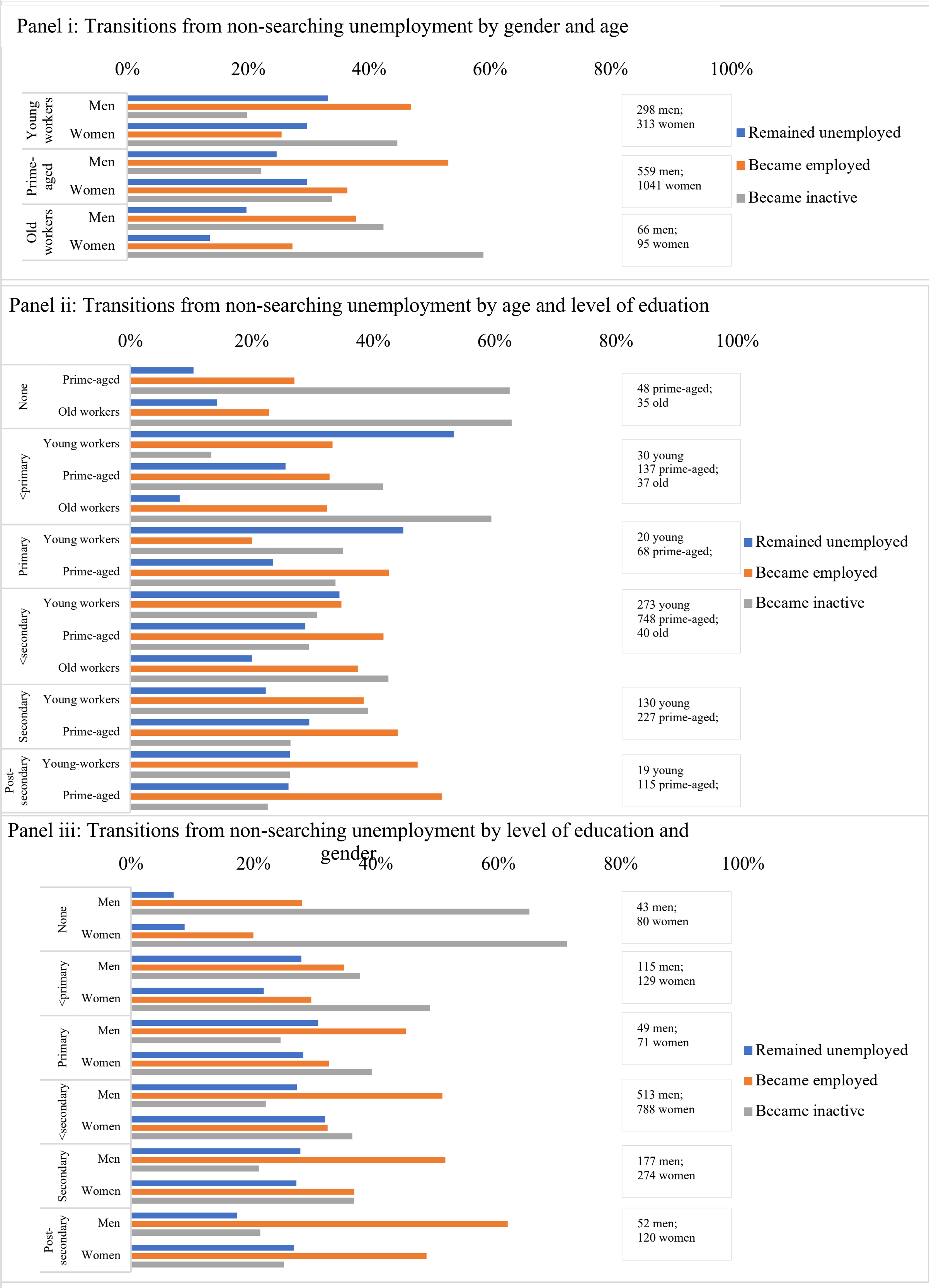
For the searching unemployed with a post-secondary qualification, those who are prime-aged are most likely to transition to employment, while their probabilities to transition to inactivity and remaining unemployed are very similar; young people are also most likely to transition to employment, while their probablities of transitioning to inactivity or remaining unemployed are similar (they are more likely to transition to inactivity, but it bears noting that the number of observations for this group is relatively small).

For the searching unemployed who at most completed their secondary education, those who are prime-aged are most likely to transition to employment, with their probablities of transitioning to inactivity and remaining unemployed being similar; those who are young are most likely to transtion to inactivity (their probability of transitioning to employment is only slightly lower), and are least ikely to remain unemployed. For the searching unemployed who have not completed secondary education, those who are prime-aged are most likely to transition to employment, while their probabilities of remaining unemployed and transitioning to inactivitvity are very similar; for those who are young, the three transition probabilities are very similar, while those who are old are most likely to transition to employment, followed by transitioning to inactivity (but it bears noting that the sample size for this group is very small).

The transitions by gender and level of education show that men and women tend to be least likely to remain unemployed, rather than transitioning to either employment or inactivity, for most levels of education. Women with no education to completed secondary education are more likely to transition to inactivity than employment, with the differences in the transition rates to inactivity and employment becoming smaller as the level of education increases. Only if they held a post-secondary qualification are women more likely to transition to employment than to inactivity, while still being least likely to remain unemployed. Men with a post-secondary level of education are also more likely to transition to employment than to inactivity, but they are much more likely to do so than women. And, just like women with no and incomplete primary education, men with these levels of education are more likely to transition to inactivity than to employment. But unlike women with completed primary and completed secondary levels of education, men with these levels of education are more likely to transition to employment than to inactivity. Furthermore, men are also more likely to transition to employment, rather than remain unemployed, if they had an incomplete level of secondary education.

Next, Figure 4.1d below shows transitions from non-searching unemployment, conditioned on the levels of the following pairs of variables: (i) age and gender; (ii) age and level of education; (iii) gender and level of education.

Figure 4.1d Transitions from non-searching unemployment (by age and gender, by level of education and age, and by level of education and gender)



Source: Author's own calculations using NIDS (W3 and W4) data. Notes: Numbers next to bars are the number of observations for those groups. Young workers are between the ages of 15 to 25 years old, prime-aged workers are 25 to 50 years old and old workers are 51 to 60 years old. Categories with very few observations have been excluded from the graphs to avoid the distortion of the figure. Pension-aged workers (above 60 years old) are excluded on Panel i - Of the 21 observations for men who were searching unemployed in wave 3, 4 (19%) became employed and 17 (81%) became inactive in wave 4. There were 29 pension-aged women who were searching unemployed in wave 3, of which 2 (7%) became employed and 27 (93%) became inactive in wave 4.

The transition rate patterns shown in Figure 4.1d above are very similar to the patterns shown in Figure 4.1c (searching unemployed transitions). The differences are predominantly in the transition rates for each category, but there are a few differences in transition patterns: the old non-searching unemployed with an incomplete secondary education are most likely to transition to inactivity; to the old searching unemployed workers were most likely to transition to employment. Young and prime-aged non-searching unemployed, who have a post-secondary education, are more likely to remain unemployed than the young and prime-aged searching unemployed with the same level of education. Furthermore, non-searching unemployed men who have completed primary or completed secondary education are more likely to remain unemployed and less likely to transition to inactivity, compared to searching unemployed men who have completed primary or completed secondary education.

As discussed above, the transition rates presented in Figures 4.1a-d indicate that these transition rates tend to differ by age, level of education and gender. To determine if age, level of education and gender are independent of the transition from unemployment to employment (u2e), I performed chi-squared independence tests. For the searching unemployed, a chi-squared statistic of 25 (p-value of less than 0.00) indicated that gender and the transition to employment are not independent; for the non-searching unemployed, I obtained a chi-squared statistic of 24.4 (p-value of less than 0.00), which also indicates that this transition is not independent of gender.

Next, Table 4.1b below presents chi-squared test statistics, and their p-values, for tests of independence between the transition to employment from searching and non-searching unemployment, and (i) level of education and (ii) age (young, prime-aged, old).

Table 4.1b Chi-squared independence statistics for transitions from unemployment (searching and non-searching) to employment and (i) level of education and (ii) age (category)

	Searching unemployment			Non-searching unemployment		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Education	17.3 (0.004)	15.7 (0.008)	16.3 (0.006)	19.3 (0.002)	15.8 (0.007)	16.5 (0.001)
Age	19.0 (0.000)	7.0 (0.074)	22.9 (0.000)	17.6 (0.000)	8.0 (0.046)	16.5 (0.001)

Source: Author's calculations using NIDS (W3 and W4) data. Notes: (1) = men and women; (2) = men; (3) = women. Chi-squared is the chi-squared test statistic for the test that the transition and education, as well as the transition and age are statistically independent (with the p-value of the test statistic in parentheses).

The chi-squared test statistics and p-values show that the transition from unemployment to employment is not independent of education or age, for both the searching and non-searching unemployed; for men and women jointly, and for men and women separately. The only p-value that exceeded 5% was for the test of independence between the transition to employment and age, for men who are searching unemployed.

I also performed chi-squared independence tests to determine if age, level of education and gender are independent of the transition from unemployment to inactivity (u2n). For the searching unemployed, a chi-squared statistic of 7.5 (p-value of less than 0.01) indicates that gender and the transition to inactivity are not independent; for the non-searching unemployed, I obtained a chi-squared statistic of

13.5 (p-value of less than 0.00), which also indicates that this transition is not independent of gender.

Table 4.1c below presents chi-squared test statistics, and their p-values, for tests of independence between the transition to inactivity from searching and non-searching unemployment, and (i) level of education and (ii) age (young, prime-aged, old).

Table 4.1c Chi-squared independence statistics for transitions from unemployment (searching and non-searching) to inactivity and (i) level of education and (ii) age (category)

	Searching unemployment			Non-searching unemployment		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Education	24.33 (0.00)	12.80 (0.03)	22.17 (0.00)	67.70 (0.00)	30.29 (0.00)	46.94 (0.00)
Age	24.44 (0.00)	10.03 (0.02)	20.53 (0.00)	88.28 (0.00)	43.48 (0.00)	59.12 (0.00)

Source: Author's calculations using NIDS (W3 and W4) data. Notes: (1) = men and women; (2) = men; (3) = women. Chi-squared is the chi-squared test statistic for the test that the transition and education, as well as the transition and age are statistically independent (with the p-value of the test statistic in parentheses).

The results from the chi-squared test statistics and p-values also show that the transitions from unemployment to inactivity, for the searching and non-searching unemployed, are not independent of education or age, for men and women jointly, and for men and women separately.

Next, I estimate and compare mean reservation wages for the unemployment transitions. For the searching unemployed, the mean reservation wage of those who remain unemployed is almost R2 660 per month (615 observations), while the mean reservation wage of those who transition to employment is about R3 334 per month (838 observations) -- which is 25% higher, and statistically significant at 1%.

Furthermore for the non-searching unemployed, the mean reservation wage is about R 2 611 per month (647 observations) for those who remain unemployed, while it is about R3 364 per month (940 observations) for those who transition to employment – which is 28% higher, and statistically significant at 1%. This result is in line with the findings of Collier (2005) and Brown and Taylor (2011), and contradicts the theoretical model of job search theory, which predicts higher reservation wages being associated with a lower probability of transitioning to employment.

Table 4.1d below provides the mean reservation wages by level of education, age group, and gender for those who remain unemployed and those who become employed. This table also reports the difference in the means, and if the reported differences are statistically significant.

Table 4.1d T-tests for differences in mean reservation wages: transitions from unemployment to employment (by education, age and gender)

Variable	Searching unemployment			Non-searching unemployment		
	1	2	3	1	2	3
	Mean (n=)	Mean (n=)	Difference	Mean (n=)	Mean (n=)	Difference
Education						
None	1440.0 (5)	1738.9 (18)	-298.9	1863.6 (11)	1987.5 (24)	-123.9
<Primary	1526.3 (38)	2227.0 (61)	**-700.7**	1439.6 (53)	2184.6 (68)	***-744.9***
Primary	2035.5 (31)	2450.0 (48)	**-414.5**	1990.7 (43)	2429.6 (54)	*-438.9*
<Secondary	2539.2 (294)	2912.2 (404)	**-372.9**	2454.8 (356)	3014.0 (458)	***-559.2***
Secondary	3301.1 (94)	4082.1 (173)	-781.0	3251.2 (121)	4146.6 (191)	-895.4
Post-secondary	3467.3 (52)	4665.9 (133)	-1198.6	3833.3 (60)	4573.4 (144)	-740.1
Age						
Young workers	2812.7 (122)	3716.3 (135)	-903.6	2791.7 (150)	3623.1 (169)	-831.4
Prime-aged workers	2604.8 (374)	3206.3 (642)	***-601.5***	2534.2 (463)	3218.4 (696)	***-684.2***
Old workers	2715.8 (19)	3914.3 (56)	-1198.5	2836.4 (33)	4167.2 (67)	-1330.8
Pension-aged workers	3500.0 (1)	2540.0 (5)	960.0	3500.0 (1)	3862.5 (8)	-362.5
Gender						
Men	3027.9 (190)	3935.9 (400)	*-908.0*	2992.4 (229)	3949.5 (437)	**-957.2**
Women	2445.2 (326)	2780.1 (438)	**-334.9**	2401.8 (418)	2855.9 (503)	***-454.1***

Source: Author's calculations using NIDS (W3 and W4) data. Notes: (1) = remain unemployed; (2) = become employed. ***Bold italic***, **bold**, *italic* denotes p-values less than 0.01, 0.05 and 0.1, respectively. Numbers in parentheses indicate the number of observations. Numbers may not add up due to rounding.

Irrespective of level of education, age group or gender, for both the searching and non-searching unemployed, the mean reservation wages of those who transition to employment are greater than the mean reservation wages of those who remain unemployed (with the exception of the difference between pension-aged workers, for the searching unemployed). Several of these differences in mean reservation wages are statistically significant at conventional levels. For both the searching and non-searching unemployed with either: (i) less than completed primary education, (ii) or with completed primary education, (iii) or with incomplete secondary education, those who transition to employment have statistically significantly higher mean reservation wages than those who remain unemployed. Prime-aged searching and non-searching unemployed who transition to employment have statistically significantly higher mean reservation wages than the prime-aged unemployed who remain unemployed. Furthermore, searching and non-searching unemployed men (women) who transition to employment have statistically significantly greater mean reservation wages than unemployed men (women) who remained unemployed.

Next, I estimate differences between mean reservation wages for those who remain unemployed and those who become economically inactive. For the searching unemployed, those who remain unemployed have a mean reservation wage that is 13% lower than the mean reservation wage of those who become inactive, and this difference is statistically significant at 10%. For the non-searching unemployed, those who remain unemployed have a mean reservation wage that is only 2.5% lower than the mean reservation wage of those who become inactive, and this difference is not statistically significant.

Table 4.1e below provides the mean reservation wages by level of education, age group, and gender for those who remain unemployed and those who become inactive. This table also reports the differences in the means, as well as whether these differences are statistically significant at conventional levels.

Table 4.1e T-tests for differences in mean reservation wages: transitioning from unemployment to inactivity (by education, age and gender)

Variable	Searching unemployed			Non-searching unemployed		
	(1)	(2)	(3)	(1)	(2)	(3)
	Mean (n=)	Mean (n=)	Difference	Mean (n=)	Mean (n=)	Difference
Education						
None	1440.0 (5)	1565.1 (63)	-125.1	1863.6 (11)	1568.5 (54)	295.1
<Primary	1526.3 (38)	2048.1 (134)	*-521.8*	1439.6 (53)	2741.6 (101)	-1302.0
Primary	2035.5 (31)	2476.6 (94)	-441.1	1990.7 (43)	2360.0 (55)	-369.3
<Secondary	2539.2 (294)	2731.0 (713)	-191.7	2454.8 (356)	2436.3 (355)	18.4
Secondary	3301.1 (94)	3730.7 (309)	-429.7	3251.2 (121)	3389.5(143)	-138.3
Post-secondary	3467.3 (52)	4401.4 (188)	-934.1	3833.3 (60)	3632.7 (55)	200.6
Age						
Young workers	2812.7 (122)	3141.0 (271)	-328.2	2791.7 (150)	2588.8 (152)	202.9
Prime-aged workers	2604.8 (374)	2997.2 (1085)	**-392.4**	2534.2 (463)	2582.5 (485)	-48.2
Old workers	2715.8 (19)	3178.7 (122)	-462.9	2836.4 (33)	3506.8 (88)	-670.4
Pension-aged workers	3500.0 (1)	1933.3 (24)	1566.7	3500.0 (1)	2268.4 (38)	1231.6
Gender						
Men	3027.9 (190)	3586.6 (596)	-558.7	2992.4 (229)	2888.9 (217)	103.4
Women	2445.2 (326)	2648.7 (906)	-203.4	2401.8 (418)	2589.6 (546)	-187.8

Source: Author's calculations using NIDS (W3 and W4) data. Notes: (1) = remain unemployed; (2) = become inactive. ***Bold italic***, **bold**, *italic* denotes p-values less than 0.01, 0.05 and 0.1, respectively. Numbers in parentheses indicate the number of observations. Numbers may not add up due to rounding.

For the searching unemployed, those who become economically inactive have higher mean reservation wages than those who remain unemployed, irrespective of the level of education, age and gender (the only exception being pension-aged workers). Only two of these differences in mean reservation wages are statistically significant. For people with less than a complete primary education, those who become inactive have significantly higher mean reservation wages than those who remain unemployed. And those who are prime-aged and become inactive have statistically significantly higher mean reservation wages than the prime-aged who remain unemployed.

For the non-searching unemployed, no clear patterns emerged as to differences in mean reservation wages between those who remain unemployed and those who become inactive. And none of these differences in mean reservation wages are statistically significant at conventional levels.

4.3 Duration of unemployment and reservation wages

This subsection presents and discusses descriptive statistics about the duration of unemployment in the third and fourth waves of NIDS. Table 4.1f below shows the distribution of the labour market status of those who were long-term unemployed (at least 12 months since the person last worked) and those who were short-term unemployed (less than 12 months since the person last worked) in waves 3 and 4.

Table 4.1f Duration by labour market status for wave 3 and 4

Duration	Labour market status			
	Searching unemployed	*Non-searching unemployed*	*Inactive*	*Total*
Wave 3				
Less than 12 months	100 (69.4)	10 (6.9)	34 (23.6)	144 (100.0)
More than 12 months	143 (27.2)	38 (7.2)	344 (65.5)	525 (100.0)
Total	243 (36.3)	48 (7.2)	378 (56.5)	669 (100.0)
Wave 4				
Less than 12 months	142 (56.6)	20 (8.0)	89 (35.5)	251 (100.0)
More than 12 months	168 (32.2)	28 (5.4)	325 (62.4)	521 (100.0)
Total	310 (40.2)	48 (6.2)	414 (53.6)	772 (100.0)

Source: Author's own calculations using NIDS (W3 and W4) data. Notes: Values in parentheses are percentages.

While most short-term unemployed are searching unemployed, and most long-term unemployed are economically inactive in waves 3 and 4, there are noticeable changes in the distributions of labour market status by unemployment duration between waves 3 and 4. In wave 4, the proportion of short-term unemployed who are searching unemployed is more than 10 percentage points less than in wave 3, while the proportion of short-term unemployed who are economically inactive is more than 10 percentage points higher. Furthermore, the proportion of long-term unemployed who are searching unemployed is 5 percentage points higher in wave 4, while the proportions of long-term unemployed who are non-searching unemployed or economically inactive are about two and three percentage points lower, respectively.

The three panels of Figure 4.1e below show the rate of long-term unemployment by age, level of education and gender, for waves 3 and 4 of NIDS.

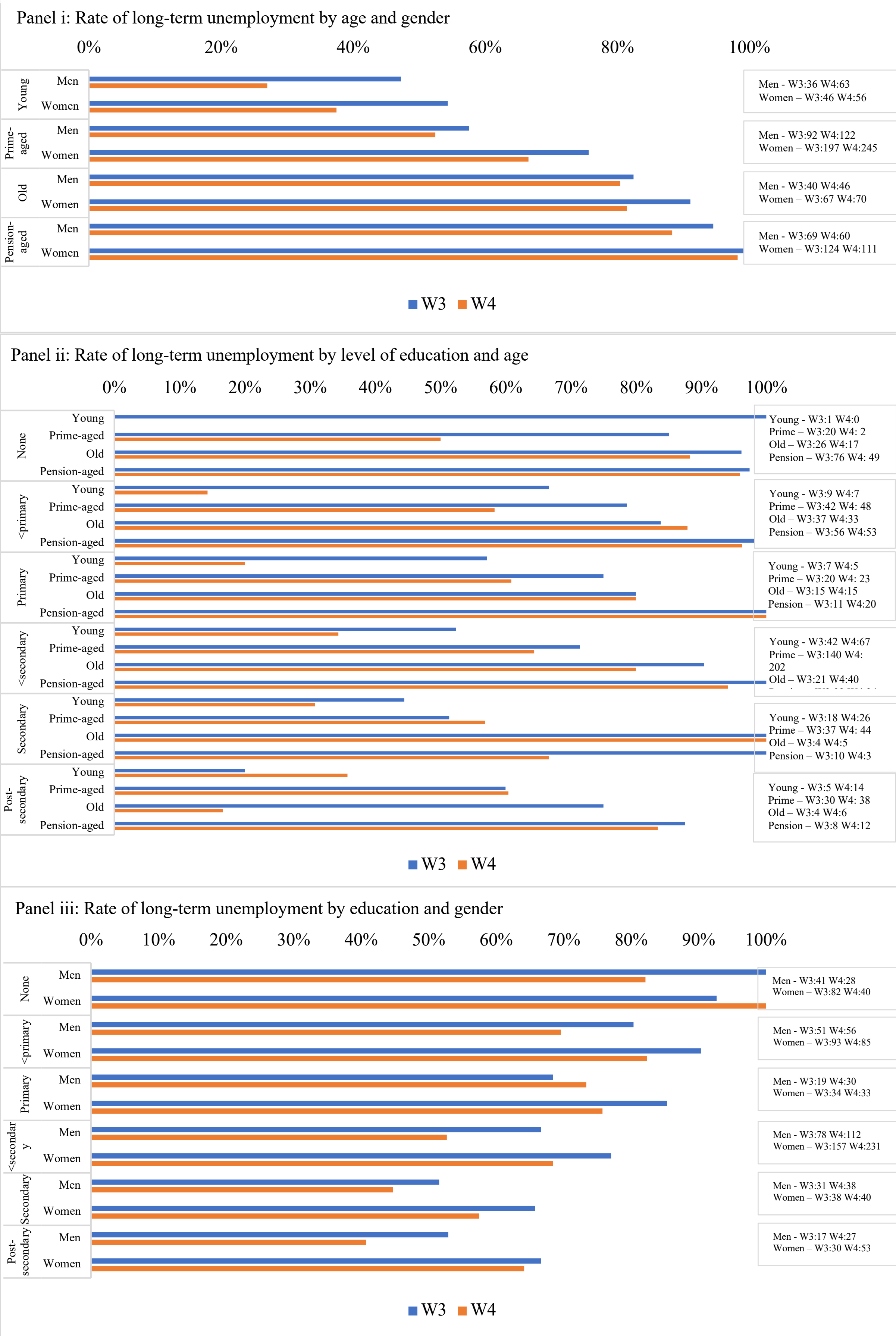
Figure 4.1e Rate of long-term unemployment by age, education and gender

Source: Author's own calculations using NIDS (W3 and W4) data. Notes: The total number of observations for wave 3 is 671 and for wave 4 is 773. Numbers above bars are the number of observations for those groups. Young workers are between 15 and 25 years old, prime-aged workers are between 25 and 50 years old, and old workers are between 51 and 60 years old.

As Figure 4.1e shows, the rate of long-term unemployment is consistently lower in wave 4 than it is in wave 3. This is true across age groups, level of education and gender. The rate of long-term unemployment increases with age in waves 3 and 4. The decrease in the rate of long-term unemployment in wave 4 is particularly large for young workers. Furthermore, in both waves 3 and 4, long-term unemployment decreases as the level of education increases from none to completed secondary. In both waves, the rate of long-term unemployment, for those with a post-secondary education, is slightly higher than for those with a secondary education. And women are more likely to be long-term unemployed than men in both waves.

To further examine how long-term unemployment varies with age, gender and level of education, Figure 4.1f below shows the rate of long-term unemployment conditioned on the levels of the following pairs of variables: (i) age and gender; (ii) age and level of education and (iii) gender and level of education.

Figure 4.1f Rate of long-term unemployment (by age and gender, age and level of education, and level of education and gender)



Source: Author's own calculations using NIDS (W3 and W4) data. Notes: Numbers next to bars are the number of observations for those groups. Young workers are 15 to 25 years old, prime-aged workers are between 25 and 50 years old and old workers are between 51 and 60 years old.

For both men and women, the rate of long-term unemployment increases with age. Women are more likely to be long-term unemployed than men across all age groups. In both waves, the largest difference in the rate of long-term unemployment between men and women is for prime-aged workers. In wave 3, the smallest difference in the rate of long-term unemployment between men and women is for those who are pension-aged, while in wave 4, it is for those who are old workers.

In both waves 3 and 4, the rate of long-term unemployment increases with age, irrespective of level of educational attainment - except for the workers with no schooling. For the workers with no-schooling, the percentage of long-term unemployment is high for all age groups in wave 3. It should be noted that for some of the age categories there are very few long-term unemployed workers with no schooling in wave 4 (e.g. 0 for young workers and 2 for prime-aged workers).

Overall, the rate of long-term unemployment tends to decrease with the level of education for both men and women, in both waves, with the following exceptions: in wave 3, men with post-secondary education are slightly more likely to be long-term unemployed than men with a complete secondary education, while this is also true for women in waves 3 and 4. Additionally, in wave 4, men with a primary education are also slightly more likely to be long-term unemployed than men with less than a primary level of education. Women are more likely to be long-term unemployed than men across all levels of education, in both waves, with the exception of those with no schooling in wave 3.

As Figure 4.1e and Figure 4.1f above show, long-term unemployment varies by age, level of education and gender. So, to determine if long-term unemployment is statistically independent of age, level of education and gender, I performed chi-squared independence tests. In both waves, I found that long-term unemployment was not independent of gender: in wave 3, I obtained a chi-squared statistic of 7.8 (p-value of less than 0.01), while in wave 4, I obtained a chi-squared statistic of 15.8 (p-value of less than 0.01).

Next, Table 4.1g **Chi-squared test statistics for tests of statistical independence between long-term unemployment and (i) education and (ii) age**below presents the chi-squared statistics, and their p-values, for independence tests between long-term unemployment and (i) level of education and (ii) age group (young, prime-aged, old, pension-aged), for waves 3 and 4.

Table 4.1g Chi-squared test statistics for tests of statistical independence between long-term unemployment and (i) education and (ii) age

	Wave 3			**Wave 4**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Education	52.2 (0.00)	28.7 (0.00)	24.9 (0.00)	43.9 (0.00)	20.1 (0.00)	27.9 (0.00)
Age	97.7 (0.00)	50.8 (0.00)	50.0 (0.00)	141.2 (0.00)	58.8 (0.00)	78.6 (0.00)

Source: Author's calculations using NIDS (W3 and W4) data. Notes: (1) = men and women; (2) = men; (3) = women. The table reports chi-squared test statistics, with their p-values in parentheses.

The p-values of the chi-squared test statistics reported in Table 4.1g Chi-squared **test statistics for tests of statistical independence between long-term unemployment and (i) education and (ii) age**show that long-term unemployment is not independent of either education or age in wave 3 or wave 4, for men and women jointly, and for men and women separately.

Table 4.1h below shows the mean reservation wages by level of education, age group and gender for the long-term and short-term unemployed, for waves 3 and 4.

This table also shows the difference in the means and if these differences are statistically significant.

Table 4.1h T-tests for differences in mean reservation wages: duration of unemployment (by education, age and gender)

Variable	Wave 3			Wave 4		
	(1)	(2)	(3)	(1)	(2)	(3)
	Mean (n=)	Mean (n=)	Difference	Mean (n=)	Mean (n=)	Difference
<u>*Education*</u>						
No Schooling	1333 (3)	2089 (18)	-755	100 (1)	1625 (4)	-1525
Incomplete primary	1907 (14)	2113 (23)	-206	2155 (21)	1974 (19)	181
Complete primary	2243 (7)	1942 (12)	301	4029 (7)	2700 (15)	1329
Incomplete secondary	2830 (47)	2911 (82)	-81	3302 (83)	2872 (104)	430
Complete secondary	7013 (23)	7025 (20)	-12	3432 (28)	4478 (23)	-1046
Post-secondary	4001 (15)	3962 (13)	40	6509 (22)	5932 (25)	577
<u>*Age*</u>						
Young workers	5116 (31)	2903 (31)	2213	3378 (58)	4838 (21)	-1461
Prime-aged workers	3135 (70)	2689 (110)	445	3516 (98)	3197 (147)	319
Old workers	3100 (7)	6018 (22)	-2918	10500 (4)	3222 (18)	***7278***
Pension-aged workers	1000 (1)	4400 (5)	-3400	2250 (2)	1250 (4)	1000
<u>*Gender*</u>						
Men	4904 (51)	4514 (390)	390	4292 (78)	4067 (73)	225
Women	2597 (58)	2436 (105)	160	3002 (84)	2885 (117)	116

Source: Author's calculations using NIDS (W3 and W4) data. Notes: (1) = short-term unemployed; (2) = long-term unemployed. ***Bold italic***, **Bold**, *Italic* denotes p-values less than 0.01, 0.05 and 0.1, respectively. Numbers in parentheses indicate the number of observations. Numbers may not add up due to rounding

In wave 3, the mean reservation wages of the long-term unemployed are greater than the mean reservation wages of the short-term unemployed, for those with a completed primary education, those with post-secondary education, young workers, prime-aged workers, and for men and women. While in wave 4, the mean reservation wages of the long-term unemployed are greater than the mean reservation wages of the short-term unemployed only for those with no schooling, those with complete secondary education and for young workers. But the only statistically significant difference in mean reservation wages between the long-term and short-term unemployed is for old workers in wave 4.

The results presented and described above can be summarised as follows: groups like unemployed older workers, unemployed workers with low educational attainment and unemployed women are more likely to transition to inactivity, than to transition to employment. On the other hand, unemployed men, the prime-aged unemployed and the unemployed with a post-secondary education are more likely to transition to employment than to inactivity. Furthermore, transitions to employment and transitions to inactivity are not independent of education, age or gender.

Those who become employed have higher mean reservation wages than those who remain unemployed. Workers who transition to employment have higher mean reservation wages than those who remain unemployed, similar to results obtained by Collier (2005) and Brown and Taylor (2011). This result also holds after the data is stratified by education, age and gender. While those who are searching unemployed and become inactive tend to have higher mean reservation wages than those who remain unemployed (but only two of these differences were statistically significant), no such pattern is found for the non-searching unemployed (and none of these differences are statistically significant).

Rates of long-term unemployment differ noticeably by age, level of education and gender. Women are more likely to be long-term unemployed than men. The rate of long-term unemployment increases with age for men and women. Furthermore, for men and women, the rate of long-term unemployment decreases with the level of educational attainment, up to completed secondary education. Long-term unemployment is not independent of age, education or gender. Mean reservation wages did not differ significantly between the long-term and short-term unemployed.

4.4 Conclusion

In this chapter, I presented summary and descriptive statistics for unemployment transitions and unemployment duration. These results can briefly be summarised as follows:

In terms of transitions from unemployment, older workers, workers with low educational attainment and women are more likely to transition to inactivity, than to transition to employment, while men, the prime-aged workers and those with a post-secondary education are more likely to transition to employment than to inactivity. Transitions to employment and transitions to inactivity are not independent of education, age or gender.

Furthermore, those who become employed have higher mean reservation wages than those who remain unemployed.

Finally, regarding long-term unemployment, women are more likely to be long-term unemployed than men, while the rate of long-term unemployment increases with age, as well as with the level of educational attainment (up to completed secondary education), for men and women

Chapter 5: Regression results

5.1 Introduction

In this chapter I present the results for the binomial (logit and probit) transition regressions (unemployment to employment; unemployment to inactivity), the multinomial transition regressions, as well as the results of the binomial (logit and probit) unemployment duration regressions. For the results of the binomial regressions, I present and discuss the logit and probit results for the searching unemployed, non-searching unemployed, searching unemployed including unemployment duration and the non-searching unemployed including unemployment durations. Thereafter, I present and discuss how the predicted probabilities vary as the main variables of interest (reservation wages, gender, age and education) vary. For the multinomial regression results, I present and discuss the results of the multinomial logit and – probit models for the transitions from unemployment for the searching unemployed, the non-searching unemployed, the searching unemployed including unemployment duration and the non-searching unemployed including unemployment duration. Each of the presentations and discussions above is followed by the presentation and discussion of the predicted probabilities of the main variables of interest (reservation wages, gender, age and education). For the unemployment duration results, I present and discuss the results of the regression models that include the reservation wage for wave 3 and wave 4 separately. The results are followed by the presentation and discussion of the predicted probabilities of the main variables of interest (reservation wage, gender, age and education). I conclude the chapter with a brief conclusion.

5.2 Binomial unemployment transitions results

In this section I present and discuss the results of the binomial unemployment transition models (unemployment to employment and unemployment to inactivity) estimated for the searching and non-searching unemployed, with and without long-term unemployment.

Table 5.1a presents the results for the binomial unemployment transitions of the searching unemployed without long-term unemployment: columns 1 to 4 present the results of the unemployment to employment transitions, and columns 5 to 8 present the results of the unemployment to inactivity transitions. The Wald statistic shows that the model coefficients are jointly statistically significant for all eight models reported in Table 5.1a, at the 1% level of significance.

Table 5.1a: Logit and probit estimates of binomial unemployment transitions, searching unemployment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reservation Wage*1000	*0.05*	*0.03*	*0.05*	*0.03*	0.03	0.02	0.03	0.02
Gender	***0.49***	***0.30***	***0.54***	***0.33***	***-0.40***	***-0.25***	***-0.39***	***-0.24***
Age	***0.03***	***0.02***	***0.03***	***0.02***	***0.02***	***0.01***	***0.02***	***0.01***
Education: Incomplete Primary	-0.44	-0.29	-0.41	-0.27	**-0.99**	**-0.58**	**-1.00**	**-0.59**
Education: Complete Primary	-0.27	-0.18	-0.26	-0.17	***-1.54***	***-0.92***	***-1.57***	***-0.93***
Education: Incomplete Secondary	-0.42	-0.27	-0.40	-0.26	***-1.49***	***-0.88***	***-1.50***	***-0.89***
Education: Complete Secondary	0.02	-0.01	0.50	0.02	***-1.18***	***-0.69***	***-1.19***	***-0.69***
Education: Post-secondary	0.16	0.07	0.19	0.10	**-1.24**	***-0.73***	**-1.24**	***-0.72***
Race: Asian/Indian	-1.29	-0.85	-1.14	-0.76	-1.42	-0.90	-1.30	-0.83
Race: African	-0.50	-0.34	-0.37	-0.26	-0.67	-0.43	-0.61	-0.39
Race: Coloured	-0.21	-0.16	-0.07	-0.08	0.18	0.09	0.23	0.11
Marital Status	-0.19	-0.12	-0.17	-0.10	*-0.31*	*-0.19*	*-0.29*	*-0.18*
Per capita income*1000	0.06	0.04	0.08	0.05	-0.03	-0.02	-0.02	-0.01
Urban	**0.30**	*0.18*	**0.31**	*0.18*	0.19	0.11	0.19	0.11
HH size	-0.01	-0.01	-0.02	-0.01	0.01	0.01	0.01	0.002
HH grant	-0.22	-0.14	-	-	-0.99	-0.07	-	-
HH pension	-	-	-0.22	-0.14	-	-	-0.14	-0.09
HH child	-	-	0.06	0.03	-	-	-0.003	-0.01
N	1353	1353	1353	1353	1180	1180	1180	1180
Pseudo R2	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06
Wald	90.12	94.86	89.54	94.29	90.91	97.83	90.46	97.3
P(wald)	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***	***0.00***

Notes: (1) = logit, u2e (unemployed to employed) b, HH grant; (2) = probit, u2e, HH grant; (3) = logit, u2e, HH pension and HH child grant; (4) = probit, u2e, HH pension and HH child grant; (5) = logit, u2n (unemployed to not active), HH grant; (6) = probit, u2n, HH grant; (7) = logit, u2n, HH pension and HH child grant; (8) = probit, u2n, HH pension and HH chlid grant. Robust standard errors were used to obtain test statistics; ***bold italic***, **bold**, *italic* denote p-values less than 0.01, 0.05 and 0.1, respectively. All estimated equations include provincial dummies.

The reservation wage estimates have positive coefficients for unemployment to employment transitions, indicating that job seekers with higher reservation wages are more likely to transition to employment. The coefficients are also statistically significant at a 10% level. For unemployment to inactivity transitions, the reservation wage coefficients are also positive, but not statistically significant at conventional levels.

The gender coefficients are positive for transitions to employment and negative for transitions to inactivity, which means that unemployed men are more likely to transition to employment, while unemployed women are more likely to transition to inactivity. All the gender coefficients are statistically significant at the 1% level. The coefficients for age are positive for both transitions to employment and transitions to inactivity, which indicates that older workers are more likely to transition from unemployment, either to employment or to inactivity. All the age coefficients are statistically significant at 1%.

All the education coefficients for transitions to inactivity are negative, which means that all unemployed people with some level of education are less likely to transition to inactivity than people with no schooling. These education coefficients are statistically significant at conventional levels. However, the education coefficients are not statistically significant at conventional levels for transitions to employment, but people with at least a completed secondary education are more likely to transition to employment than people with no schooling (except in the probit model that included the household receipt of government grant income variable). People with up to an incomplete secondary education are less likely to transition to employment than people with no schooling.

The marital status coefficients are negative for transitions to inactivity, which indicates that people not married or living with a partner are less likely to transition to inactivity. These coefficients are also statistically significant at 10%. The urban-rural classification coefficients are positive for transitions to employment, which means that people who stay in urban areas are more likely to transition to employment. The coefficients are statistically significant at conventional levels.

Table 5.1b presents the results for the binomial unemployment transitions of the non-searching unemployed without long-term unemployment: columns 1 to 4 represent the results of the unemployment to employment transitions and columns 5 to 8 represent the results of the unemployment to inactivity transitions. The Wald statistics indicate that the models' coefficients are jointly statistically significant for all eight models, at the 1% level of significance.

Table 5.1b: Logit and probit estimates of binomial unemployment transitions, non-searching unemployment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reservation Wage*1000	***0.07***	***0.04***	***0.07***	**0.04**	0.03	0.02	0.03	0.02
Gender	***0.52***	***0.32***	***0.56***	***0.34***	***-0.35***	***-0.21***	***-0.34***	***-0.21***
Age	***0.25***	***0.02***	***0.03***	***0.02***	***0.03***	***0.02***	***0.03***	***0.02***
Education: Incomplete Primary	-0.43	-0.27	-0.44	-0.28	**-0.84**	**-0.49**	**-0.84**	**-0.50**
Education: Complete Primary	-0.38	-0.24	-0.41	-0.26	***-1.36***	***-0.82***	***-1.35***	***-0.81***
Education: Incomplete Secondary	-0.32	-0.20	-0.34	-0.21	***-1.25***	***-0.74***	***-1.25***	***-0.74***
Education: Complete Secondary	-0.06	-0.04	-0.06	-0.05	***-1.12***	***-0.66***	***-1.12***	***-0.66***
Education: Post-secondary	0.24	0.14	0.24	0.14	***-1.05***	***-0.62***	***-1.05***	***-0.62***
Race: Asian/Indian	-1.06	-0.67	-0.99	-0.63	-1.28	-0.80	-1.26	-0.79
Race: African	-0.54	-0.34	-0.51	-0.32	-0.43	-0.27	-0.43	-0.27
Race: Coloured	-0.397	-0.25	-0.36	-0.22	0.11	0.71	0.13	0.08
Marital Status	-0.14	-0.08	-0.11	-0.07	-0.19	-0.119	-0.18	-0.11
Per capita income*1000	0.04	0.04	*0.08*	*0.05*	0.05	0.03	0.05	0.03
Urban	0.15	0.09	0.15	0.09	0.01	2E-04	0.002	-0.004
HH size	-0.02	-0.01	-0.12	-0.01	0.002	0.001	0.004	0.002
HH grant	-0.10	-0.06	-	-	0.13	0.08	-	-
HH pension	-	-	-0.16	-0.10	-	-	-0.01	-0.003
HH child	-	-	0.10	0.06	-	-	0.07	0.04
N	1586	1586	1586	1586	1410	1410	1410	1410
Pseudo R2	0.05	0.05	0.05	0.05	0.06	0.07	0.06	0.06
Wald	100.28	105.35	102.05	107.38	114.02	122.47	113.66	121.99
P(wald)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: (1) = logit, u2e (unemployed to employed) broad, HH grant; (2) = probit, u2e broad, HH grant; (3) = logit, u2e broad, HH pension and HH child grant; (4) = probit, u2e broad, HH pension and HH child grant; (5) = logit, u2n (unemployed to not active) broad, HH grant; (6) = probit, u2n broad, HH grant; (7) = logit, u2n broad, HH pension and HH child grant; (8) = probit, u2n broad, HH pension and HH chid grant. Robust standard errors were used to obtain test statistics; ***bold italic***, **bold**, *italic* denote p-values less than 0.01, 0.05 and 0.1, respectively. All estimated equations include provincial dummies.

The coefficients for the reservation wage estimates are positive for unemployment to employment transitions, indicating that job seekers with higher reservation wages are more likely to transition to employment. The coefficients are also statistically significant at conventional levels. For unemployment to inactivity transitions, the reservation wage coefficients are also positive, but not statistically significant at conventional levels.

The gender coefficients are positive for transitions to employment and negative for transitions to inactivity, which means that men are more likely to transition to employment and women were more likely to transition to inactivity. All the coefficients are statistically significant at 1%. The coefficients for age are positive for both transitions to employment and transitions to inactivity, which indicates that older people are more likely to transition from unemployment than younger people. All age coefficients were statistically significant at 1%.

None of the education coefficients are statistically significant at conventional levels for transitions to employment. It should be noted though, that for transitions to employment, the only positive education coefficients are those for post-secondary education, which means that only people with a post-secondary education are more likely to transition to employment than people with no schooling. For transitions to inactivity, all the education coefficients are negative, which indicates that all unemployed people with some level of schooling are less likely to transition to inactivity than people with no schooling. All of the education coefficients for transitions to inactivity were statistically significant at conventional levels.

Furthermore, per capita income is positively associated with transitions to employment, indicating that people in households with a higher income per capita are more likely to transition to employment. The coefficients of per capita income in the logit and probit models reported in columns 3 and 4 were statistically significant at a 10% level of significance.

Table 5.1c presents the results for binomial unemployment transitions, for the searching unemployed, including long-term unemployment. Columns 1 to 4 present the results of the unemployment to employment transitions, and columns 5 to 8 present the results of the unemployment to inactivity transitions. When long-term unemployment is included, the number of observations decreased significantly. This is because most of the unemployed report never having worked before. And the duration of unemployed cannot be measured accurately where unemployed people have never worked, as NIDS does not collect data on the date of entry into the labour force. Unfortunately, the Wald statistic indicates that the coefficients on the explanatory variables in all of these models are jointly equal to zero. I will therefore not discuss the individual coefficient estimates for any of these models.

Table 5.1c: Logit and probit estimates of binomial unemployment transitions: searching unemployment, with long-term unemployment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reservation Wage*1000	0.03	0.02	0.02	0.01	0.02	0.01	0.02	0.01
Long-term unemployment	-0.37	-0.20	-0.51	-0.31	0.75	0.46	0.81	0.49
Gender	*0.95*	*0.50*	0.77	0.41	-0.36	-0.22	-0.54	-0.34
Age	0.03	0.02	0.03	0.02	0.02	0.01	0.02	0.01
Education: Incomplete Primary	-1.94	*-1.14*	*-1.96*	*-1.18*	**-2.76**	**-1.68**	**-2.78**	**-1.67**
Education: Complete Primary	0.75	0.19	0.63	0.18	**-3.69**	**-2.23**	**-3.82**	**-2.31**
Education: Incomplete Secondary	-0.69	-0.44	-0.69	-0.43	*-2.05*	**-1.24**	*-2.07*	**-1.24**
Education: Complete Secondary	-0.38	-0.26	-0.35	-0.24	**-3.25**	***-1.96***	**-3.41**	***-1.99***
Education: Post-secondary	-0.11	-0.11	-0.22	-0.16	-2.31	-1.39	-2.40	-1.42
Race: Coloured	0.70	0.38	0.87	0.50	0.45	0.28	1.09	0.71
Marital Status	-0.89	-0.53	-0.94	-0.56	*-1.15*	**-0.72**	*-1.19*	**-0.74**
Per capita income*1000	-0.05	-0.02	-0.0001	-0.07	-0.09	-0.06	0.0002	0.09
Urban	0.09	0.05	0.11	0.05	0.62	0.37	0.50	0.31
HH size	0.03	0.02	0.09	0.05	0.001	0.002	-0.03	-0.01
HH grant	0.56	0.27	-	-	*0.98*	*0.59*	-	-
HH pension	-	-	-0.04	-0.07	-	-	-0.09	0.05
HH child	-	-	-0.37	-0.27	-	-	**1.39**	**0.82**
N	131	131	131	131	103	103	103	103
Pseudo R2	0.16	0.15	0.15	0.15	0.2	0.21	0.22	0.22
Wald	19.32	22.46	22.71	26.7	26.38	30.92	26.81	31.79
P(wald)	0.68	0.49	0.54	0.32	0.28	0.12	0.31	0.13

Notes: (1) = logit, u2e (unemployed to employed), HH grant; (2) = probit, u2e, HH grant; (3) = logit, u2e, HH pension and HH child grant; (4) = probit, u2e, HH pension and HH child grant; (5) = logit, u2n (unemployed to not active), HH grant; (6) = probit, u2n, HH grant; (7) = logit, u2n, HH pension and HH child grant; (8) = probit, u2n, HH pension and HH chlid grant. Robust standard errors were used to obtain test statistics; ***bold italic***, **bold**, *italic* denote p-values less than 0.01, 0.05 and 0.1, respectively. All estimated equations include provincial dummies.

Table 5.1d presents the results for binomial unemployment transitions for the non-searching unemployed, including long-term unemployment. Columns 1 to 4 present the results of the unemployment to employment transitions, and columns 5 to 8 present the results of the unemployment to inactivity transitions. As was the case for the model estimates reported in Table 5.1c, when long-term unemployment is included, the number of observations decreased significantly. Unfortunately, the Wald statistics indicate that the coefficients on the explanatory variables of the models for transitions to employment are jointly equal to zero. However, for the transitions to inactivity models, the Wald statistics indicate that, in these models, the coefficients on the explanatory variables are not jointly equal to zero.

Table 5.1d: Logit and probit estimates of binomial unemployment transitions, non-searching unemployment, with long-term unemployment

	1	2	3	4	5	6	7	8
Reservation Wage*1000	0.04	*0.02*	0.03	0.02	0.03	0.02	0.03	0.02
Long-term unemployment	-0.37	-0.21	-0.51	-0.31	0.82	*0.49*	*1.00*	*0.57*
Gender	**1.01**	**0.59**	*0.79*	*0.47*	-0.19	-0.12	-0.34	-0.23
Age	0.003	0.002	0.004	0.002	0.005	0.004	0.01	0.005
Education: Incomplete Primary	-1.41	-0.83	-1.15	-0.69	-1.47	*-0.95*	*-1.75*	**-1.10**
Education: Complete Primary	-0.37	-0.25	-0.19	-0.14	***-3.72***	***-2.25***	***-4.14***	***-2.50***
Education: Incomplete Secondary	-0.48	-0.30	-0.26	-0.16	*-1.52*	**-0.94**	**-1.61**	**-1.01**
Education: Complete Secondary	-0.34	-0.21	-0.08	-0.06	**-2.83**	***-1.70***	**-3.11**	***-1.81***
Education: Post-secondary	0.23	0.10	0.21	0.12	-1.56	-0.96	-1.75	-1.08
Race: White	0	0	0	0				
Race: African	-0.65	-0.39	-0.81	-0.50				
Race: Coloured	0	0	0	0	0.74	0.42	1.11	0.72
Marital Status	*-0.91*	*-0.56*	*-0.95*	*-0.58*	***-1.40***	***-0.86***	***-1.37***	***-0.82***
Per capita income*1000	0.02	0.02	-0.06	-0.03	0.34	0.2	0.63	0.36
Urban	0.0002	-0.001	0.004	-0.002	-0.32	-0.2	-0.35	-0.18
HH size	-0.03	-0.02	0.02	0.01	*-0.11*	*-0.06*	**-0.17**	**-0.10**
HH grant	*0.88*	*0.51*	-	-	***1.35***	***0.79***	-	-
HH pension	-	-	0.07	0.03	-	-	0.38	0.22
HH child	-	-	-0.36	-0.24	-	-	**1.67**	***0.94***
N	150	150	150	150	130	130	130	130
Pseudo R2	0.12	0.12	0.11	0.11	0.24	0.24	0.25	0.25
Wald	20.47	23.90	21.56	25.31	35.63	42.56	36.07	45.19
P(wald)	0.61	0.41	0.61	0.39	0.05	0.01	0.05	0.01

Notes: (1) = logit, u2e broad, HH grant; (2) = probit, u2e broad, HH grant; (3) = logit, u2e broad, HH pension and HH child grant; (4) = probit, u2e broad, HH pension and HH child grant; (5) = logit, u2n broad, HH grant; (6) = probit, u2n broad, HH grant; (7) = logit, u2n broad, HH pension and HH child grant; (8) = probit, u2n broad, HH pension and HH chid grant. Robust standard errors were used to obtain test statistics; ***bold italic***, **bold**, *italic* denote p-values less than 0.01, 0.05 and 0.1, respectively. All estimated equations include provincial dummies.

The reservation wage coefficients are positive for the unemployment to inactivity transitions, but none of the reservation wage coefficients are statistically significant at conventional levels. For transitions to inactivity, the coefficients for long-term unemployment are positive, which indicates that people who were unemployed for more than 12 months are more likely to transition to inactivity.

For transitions to inactivity, the coefficients for gender are negative, which means that women are more likely to transition to inactivity, while the coefficients for age are positive, which indicates that older people are more likely to transition to inactivity. However, none of the coefficients on gender or age are statistically significant at conventional levels.

Furthermore, all of the education coefficients are negative, which indicates that unemployed people with any schooling are less likely to transition to inactivity than people with no schooling. The education coefficients, for education levels from incomplete primary to complete secondary, are statistically significant at conventional levels, but the post-secondary coefficients are not.

The coefficients for marital status are negative, and statistically significant at 1%, which indicates that people who were married or living together are more likely to transition to inactivity than people who were not married or living together. Furthermore, the coefficients for household size are negative, and statistically significant, which means that people who were part of larger households are less likely to transition to inactivity.

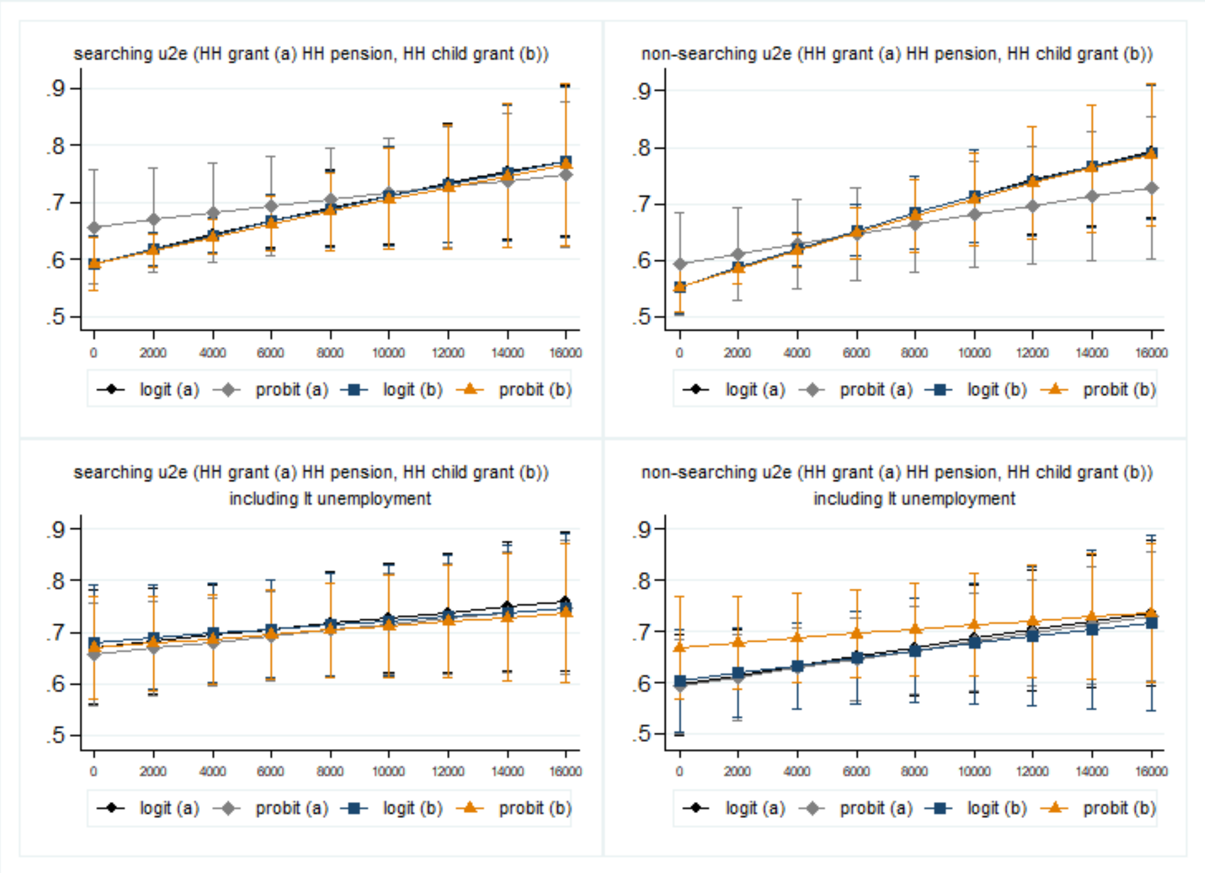
The coefficients on household receipt of income from a government grant are positive in the models for transitions to inactivity, indicating that people who were part of a household that received a government grant are more likely to transition to inactivity. These coefficients are also statistically significant at 1% for transitions to inactivity. In the transition to inactivity models, the coefficients on household receipt of a child support grant are positive, which indicates that people who were part of a household that received a child support grant are more likely to transition to inactivity. These coefficients are statistically significant at conventional levels.

To facilitate the interpretation of the coefficients reported in the tables above, I estimated the predicted probabilities of the transitions from unemployment to employment, and from unemployment to inactivity, of the model estimates reported in Tables 5.1a to 5.1d. I present and discuss the predicted transition probabilities for the reservation wage, age, gender, education and long-term unemployment, as these are my primary variables of interest, to determine how changes in these variables affect transitions from unemployment.

The figures that report the predicted probabilities show the results for the searching unemployment transitions on the left-hand side and the non-searching unemployment transitions on the right-hand side. The top row shows the predicted probabilities of the models that do not include long-term unemployment as an explanatory variable, while the bottom row shows the predicted probabilities of the models that do include long-term unemployment. In each panel, four sets of predicted probabilities are reported: the logit and probit estimates for the models that include the HHgrant dummy variable, as well as the logit and probit estimates for the models that include the HHpension and HH child grant dummy variables.

Figure 5.1a below shows the predicted probabilities of the unemployment to employment transitions for the reservation wages.

Figure 5.1a Predicted probabilities of unemployment to employment transitions by reservation wage

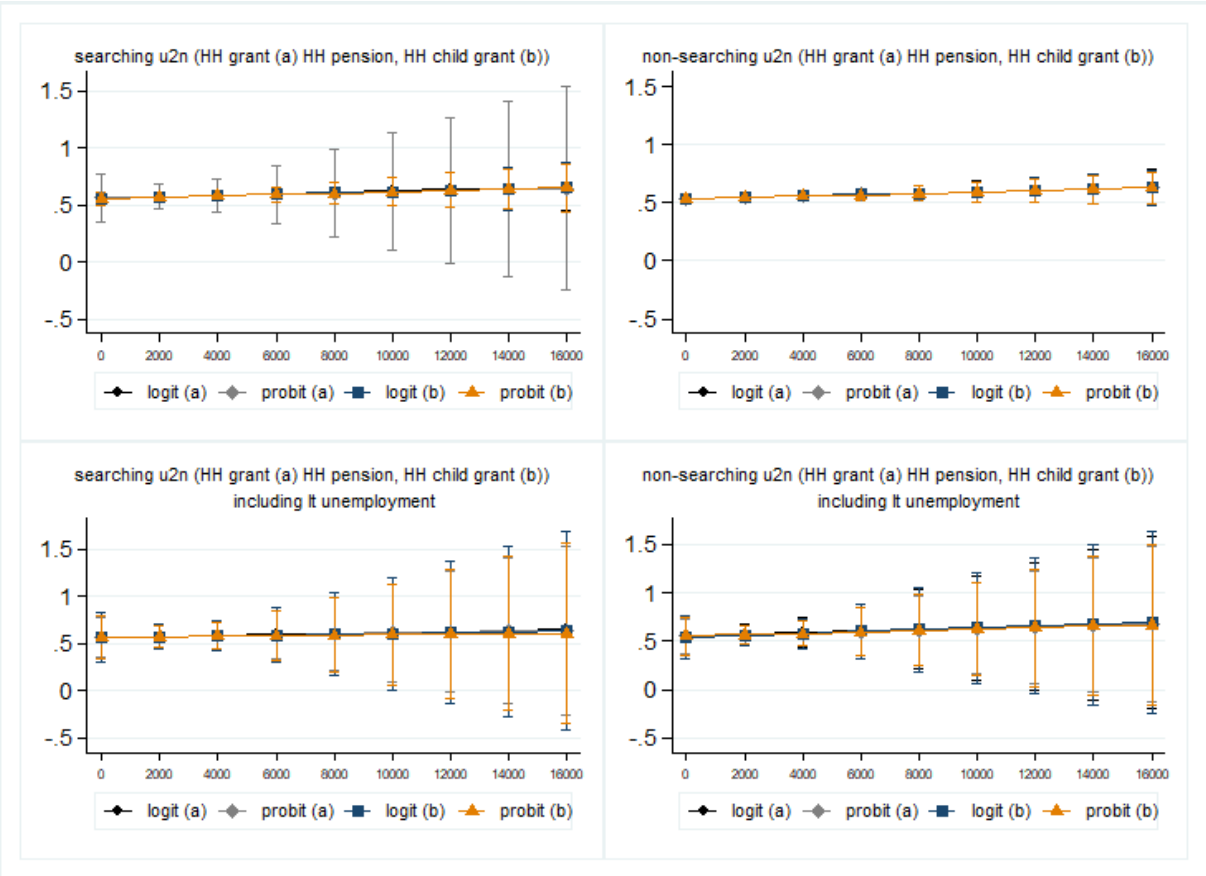


Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

Figure 5.1a shows that the predicted probabilities of transitions to employment increases, across all estimated models, as the reservation wage increases. The reservation wage coefficients are also statistically significant at conventional levels in the models that did not include long-term unemployment. Furthermore, most of the four predicted probabilities reported in each panel of the figure were very similar. These results are line with those obtained by Poterba and Summers (1995).

Figure 5.1b shows the predicted probabilities of unemployment to inactivity transitions by reservation wage.

Figure 5.1b Predicted probabilities of unemployment to inactivity transitions by reservation wage

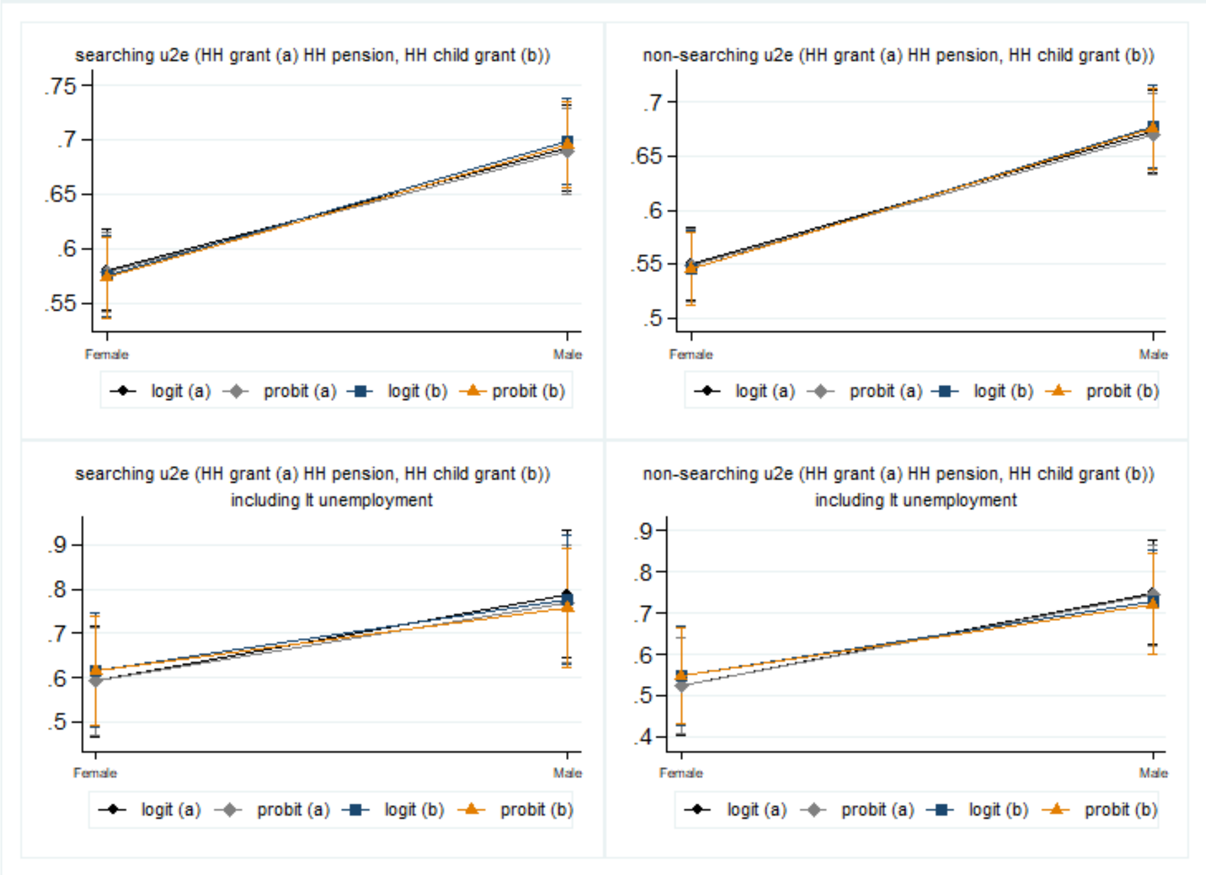


Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

Figure 5.1b shows that the predicted probabilities of transitions to inactivity increases as the reservation wage increases, and that the four predicted probabilities reported in each panel of the figure are very similar. However, none of the coefficients on the reservation wage are statistically significant in any of the transition to inactivity models.

Figure 5.1c shows the predicted probabilities of unemployment to employment transitions by gender.

Figure 5.1c Predicted probabilities of unemployment to employment transitions by gender

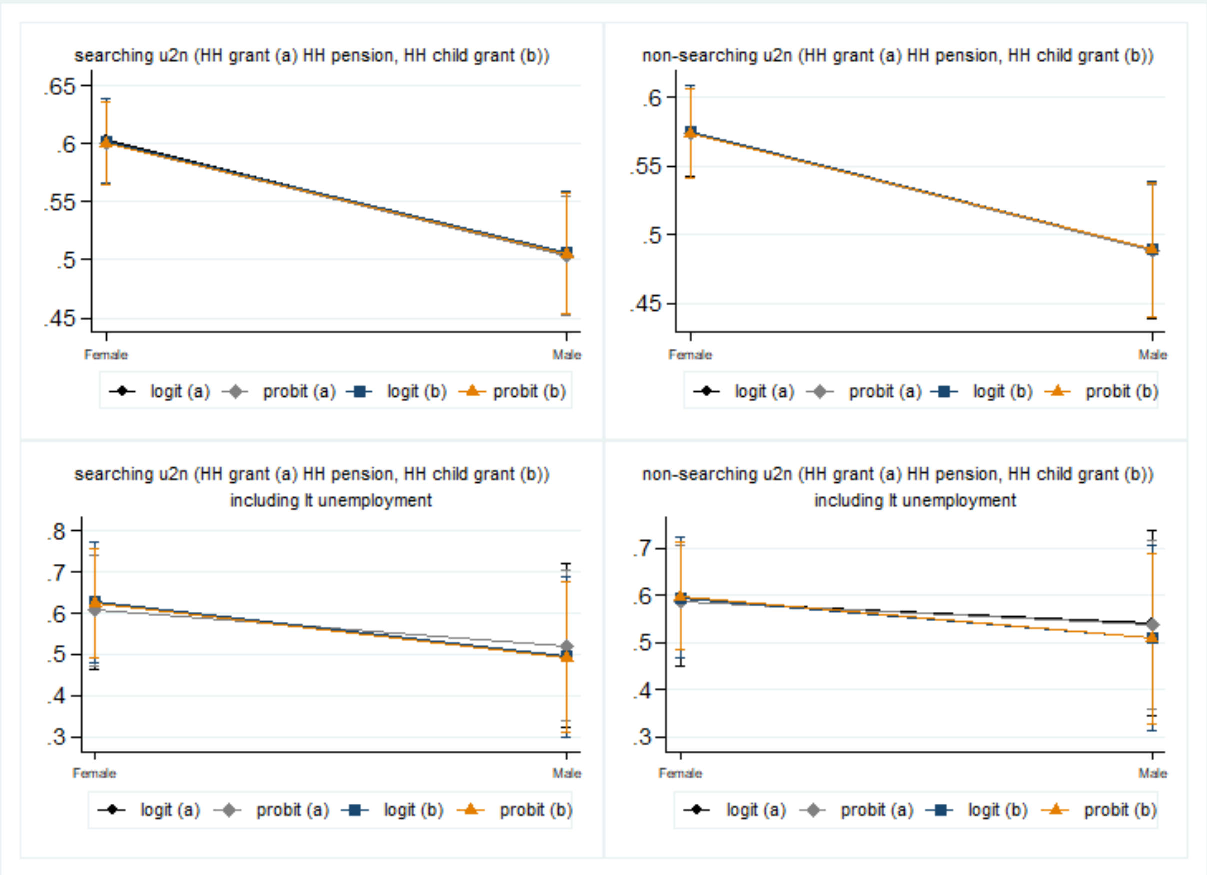


Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

Figure 5.1c shows that men have higher predicted probabilities to transition to employment than women, while all four predicted probabilities reported in each of the panels of the figure are very similar. In the models that excluded unemployment duration, gender is statistically significant These results are in line with those of Brick and Mlatsheni (2008), Mlatsheni and Leibbrandt (2015) and Dinkelman (2004).

Figure 5.1d shows the predicted probabilities of the unemployment to inactivity transitions by gender.

Figure 5.1d Predicted probabilities of unemployment to inactivity transitions by gender

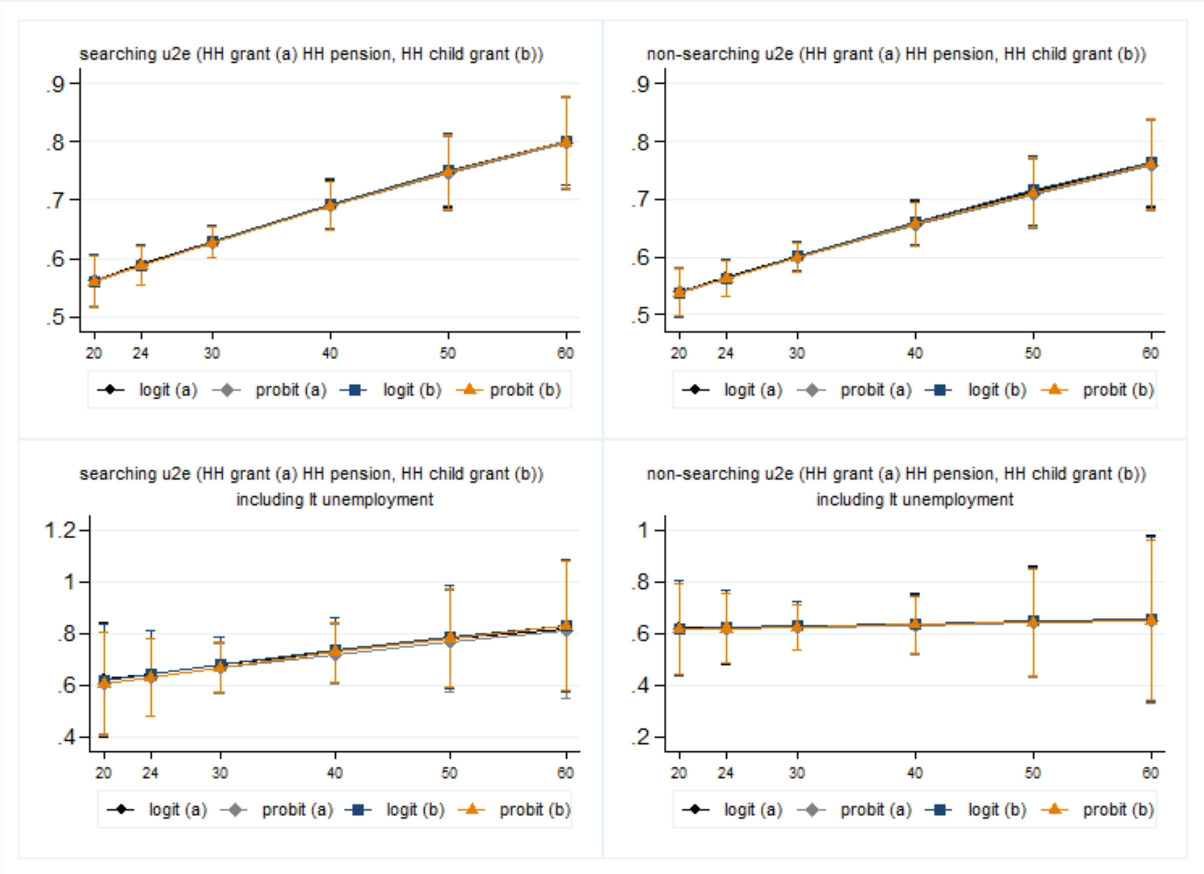


Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

Figure 5.1d above shows that women have higher predicted probabilities to transition to inactivity than men, and that the four predicted probabilities reported in each panel of the figure are very similar. Furthermore, the coefficients on gender are statistically significant at 1% in the models that excluded unemployment duration. These results are in line with those of Dinkelman (2004).

Figure 5.1e shows the predicted probabilities of unemployment to employment transitions by age.

Figure 5.1e Predicted probabilities of unemployment to employment transitions by age

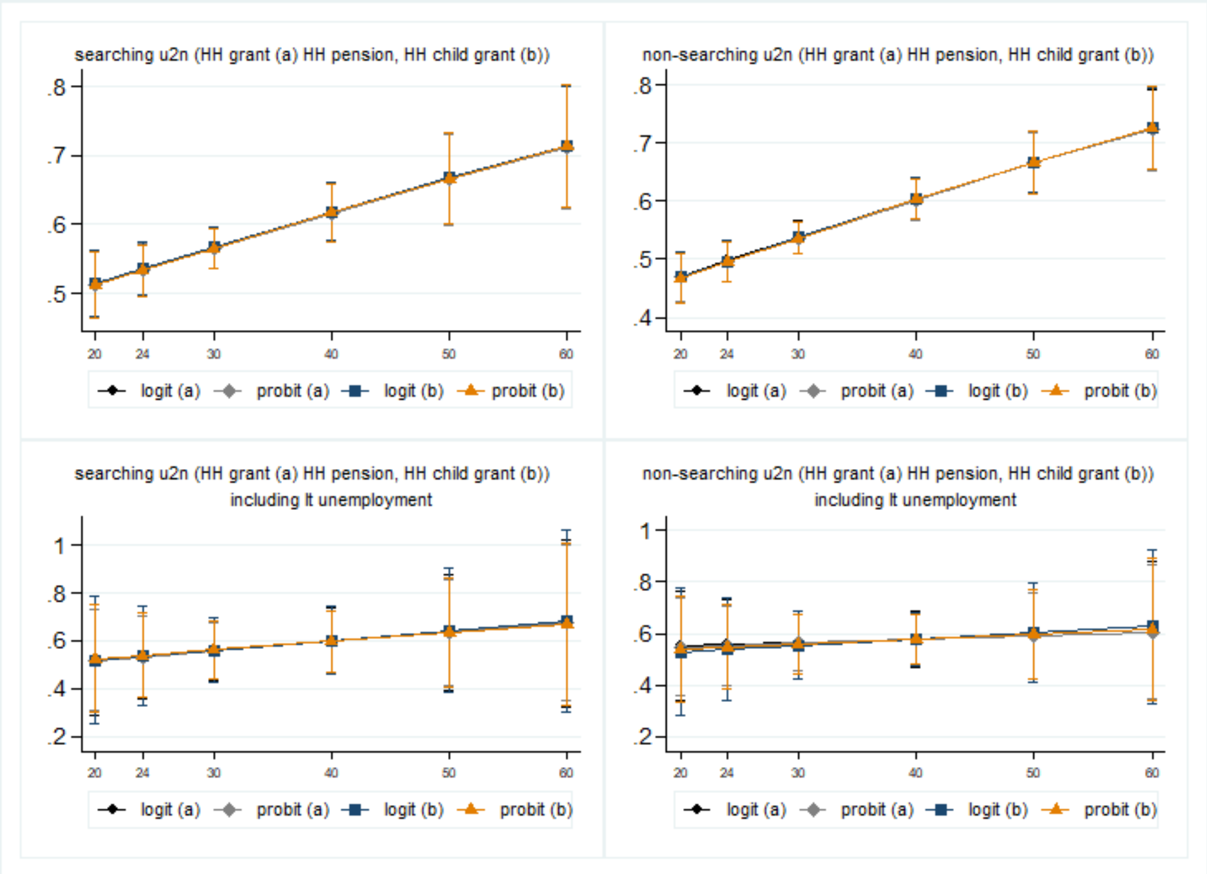


Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

Figure 5.1e shows that the predicted probability to transition to employment increases with age. Age coefficients are statistically significant at 1% in the models that excluded unemployment duration. These results are in line with those of Brick and Mlatsheni (2008), Dinkelman (2004) and Mlatsheni and Leibbrandt (2015).

Figure 5.1f shows the predicted probabilities of unemployment to inactivity transitions by age.

Figure 5.1f Predicted probabilities of unemployment to inactivity transitions by age

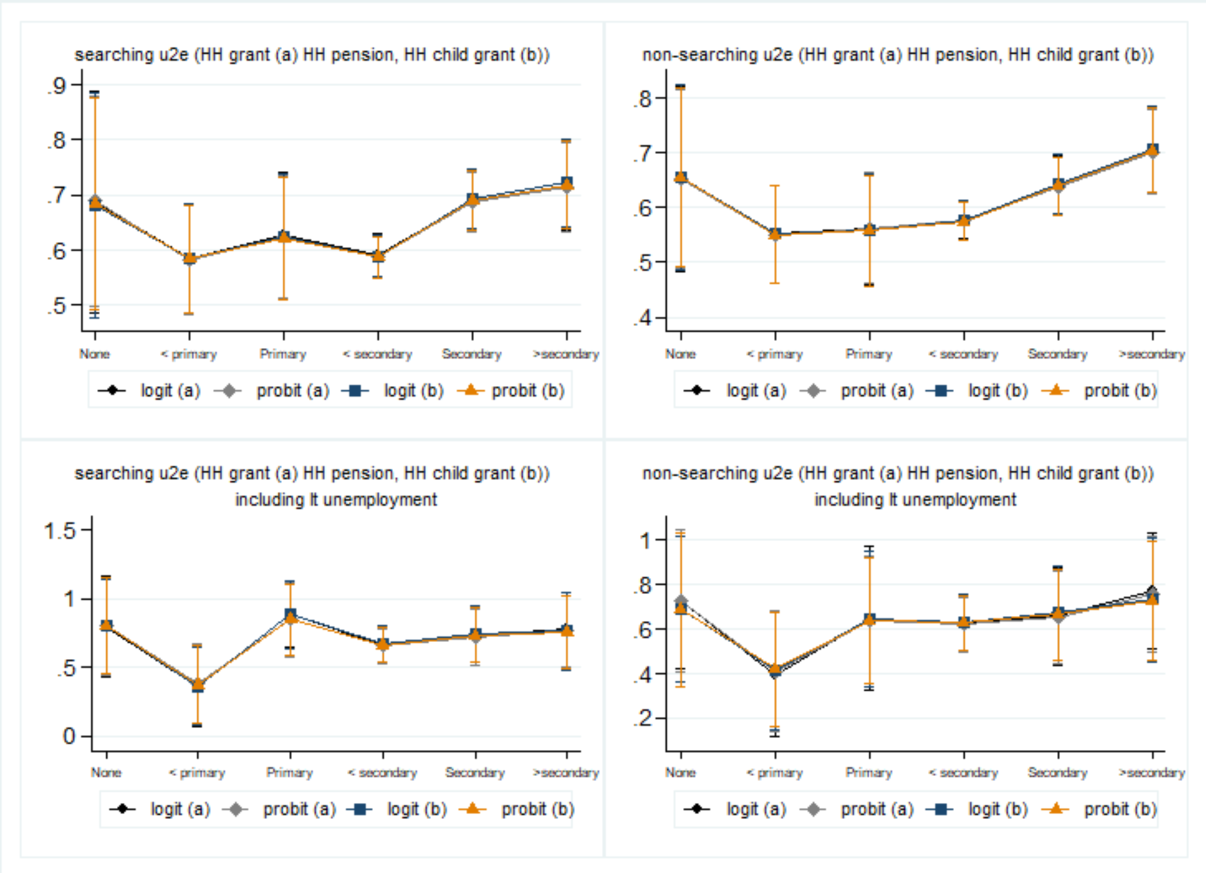


Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations

Figure 5.1f shows that the predicted probabilities to transition to inactivity increases with age (though much less pronounced for non-searching transitions to inactivity that include unemployment duration), while all four predicted probabilities in each panel of the figure are very similar. The coefficients on age are statistically significant at 1% in the models that excluded unemployment duration. These results are in line with those of Dinkelman (2004).

Figure 5.1g shows the predicted probabilities of unemployment to employment transitions by level of education.

Figure 5.1g Predicted probabilities of unemployment to employment transitions by level of education



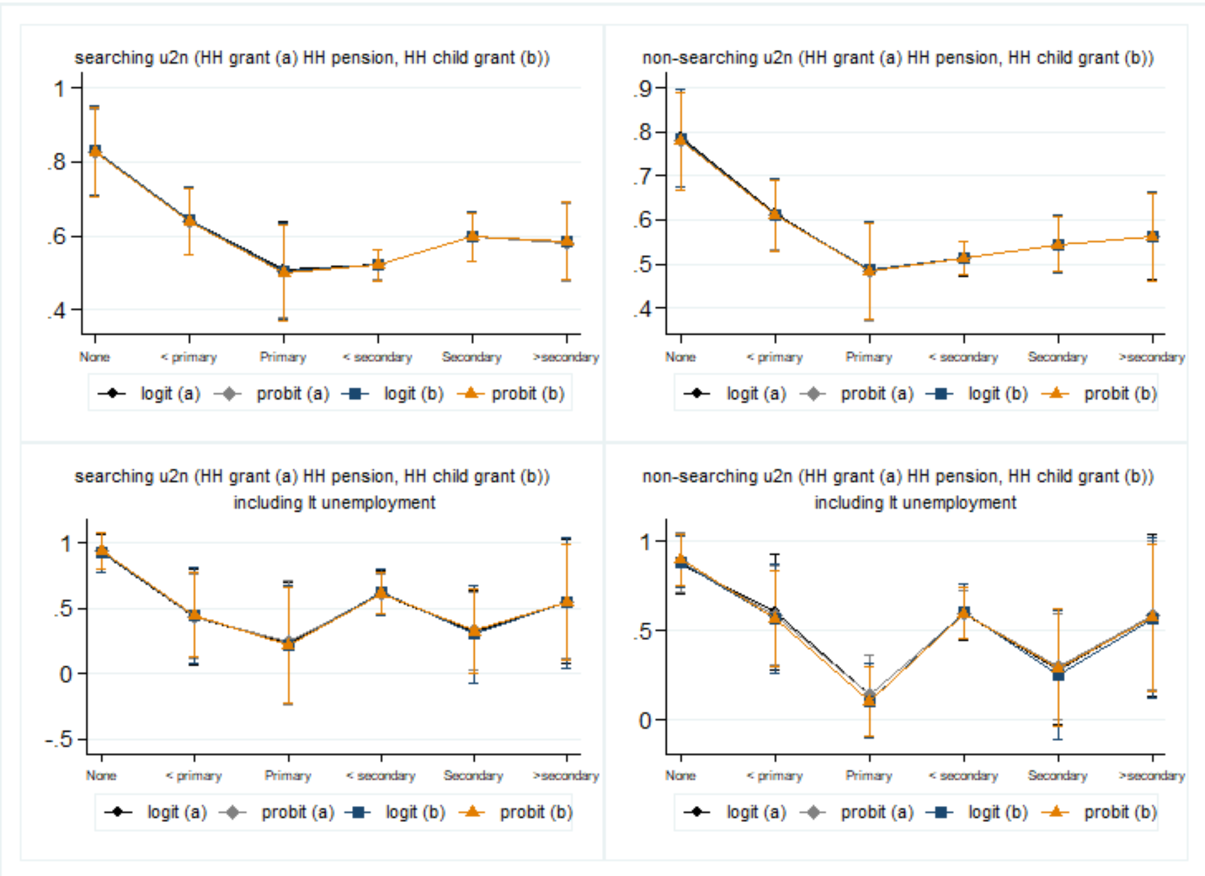
Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

Figure 5.1g shows that the predicted probabilities of transitions to employment do not increase or decrease uniformly with the level of education: predicted transition probabilities tend to decrease from no schooling to some primary schooling, while increasing from some to complete primary schooling, and noticeably increasing for completed secondary and post-secondary education. Again, the four predicted probabilities reported in each panel are very similar.

In three of the four panels of Figure 5.1g, workers with post-secondary education had the highest predicted probabilities to transition to employment, while workers with a primary education had the highest predicted probability to transition to employment in the searching unemployment model that included the duration of unemployment (row 2, column 1). Workers with an incomplete primary education consistently had the lowest predicted probabilities to transition to employment. Workers with no schooling had similar predicted probabilities to transition to employment than those workers with a completed secondary education. However, only the coefficients on incomplete primary education in the probit(a), logit(b) and probit(b) models for the searching unemployed, including the duration of unemployment in the model, were statistically significant at conventional levels.

Figure 5.1h shows the predicted probabilities of unemployment to inactivity transitions by level of education.

Figure 5.1h Predicted probabilities of unemployment to inactivity transitions by level of education



Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

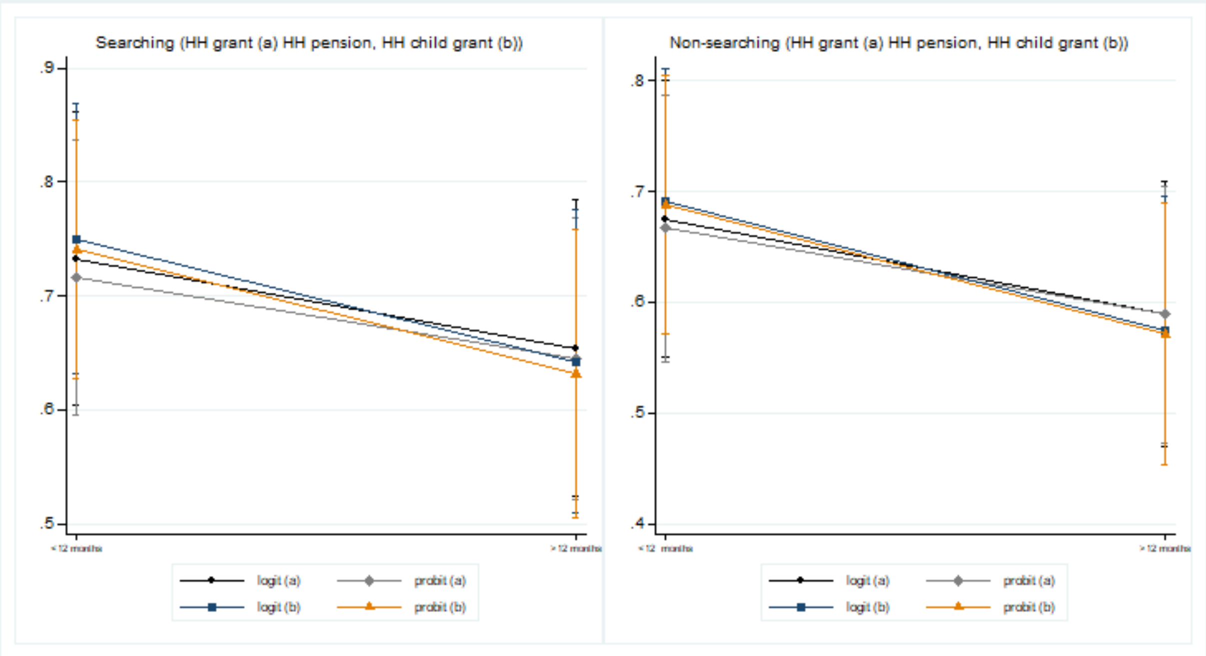
Figure 5.1h shows that workers with no schooling had the highest predicted probabilities to transition to inactivity, while workers with a completed primary education had the lowest predicted probability to transition to inactivity. In the models excluding the duration of unemployment (the two panels in top row of the figure), the predicted probability to transition to inactivity decreased from no schooling to completed primary education, before increasing again as the level of educational attainment increased beyond completed primary. All of these education coefficients were statistically significant at conventional levels in the models that excluded unemployment duration.

While the predicted probabilities in the two panels in the top row of Figure 5.1h resemble a shallow, asymmetric v, the predicted probabilities in the two panels in the bottom row of the figure have a saw-toothed pattern. In the models that included unemployment duration, the coefficients for post-secondary education were not statistically significant at conventional levels. All other coefficients (except logit(a) for non-searching unemployment) were statistically significant at conventional levels. All four predicted probabilities in each panel of Figure 5.1h are very similar.

Figures 5.1i and 5.1j show predicted probabilities of transitions to employment and inactivity by unemployment duration. Unlike the previous figures, these two figures only have one row, as all of the models for which predicted probabilities are reported in these two figures include the unemployment duration dummy. But just like the previous figures, the left-hand side column depicts predicted probabilities for models including the searching unemployed, while the right-hand side columns are for models including the non-searching unemployed. Also, as in the previous figures, each panel reports four predicted probabilities: probit and logit estimates of models including a household grant receipt dummy, and models including separate dummies for household receipt of income from government old-age pensions or child support grants.

Figure 5.1i shows the predicted probabilities of unemployment to employment transitions by duration of long-term unemployment.

Figure 5.1i Predicted probabilities of unemployment to employment transitions by duration of unemployment

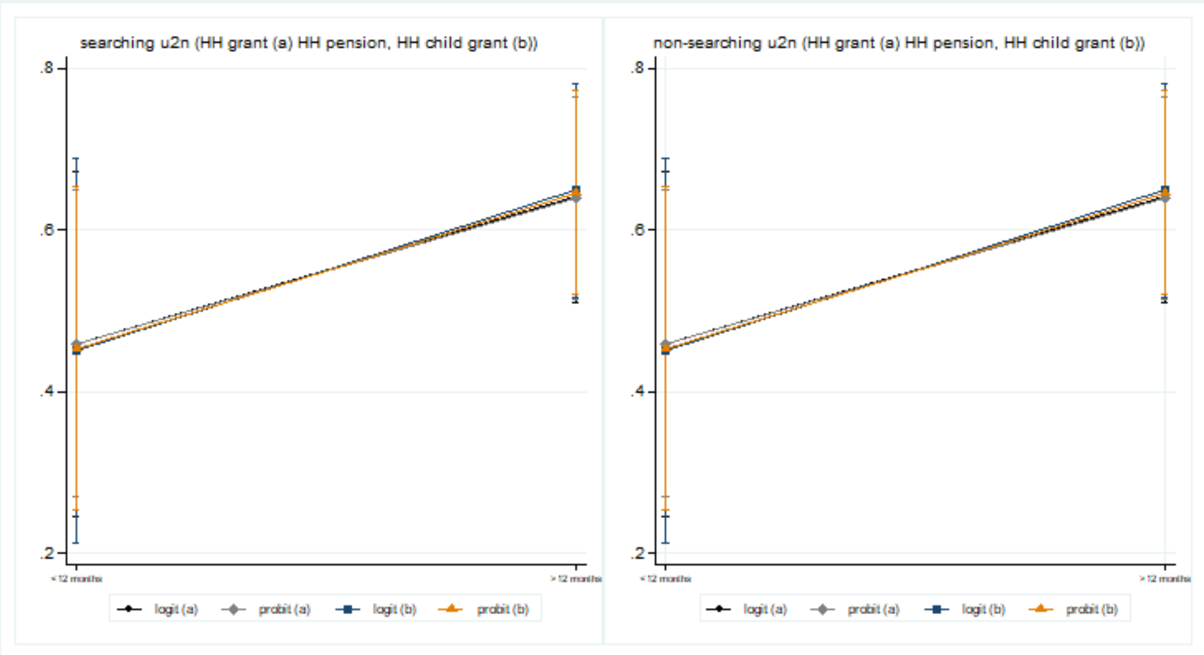


Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

Figure 5.1i shows that those who had been unemployed for more than 12 months have a lower predicted probability to transition to employment than those who had been unemployed for less than 12 months, while the four predicted probabilities reported in each panel are very similar. These results imply negative duration dependence: the probability to transition to employment decreases as the duration of unemployment increases. However, the coefficient on the long-term unemployment dummy is not statistically significant at conventional levels for the unemployment to employment transitions.

Figure 5.1j shows the predicted probabilities of unemployment to inactivity transitions by duration of unemployment.

Figure 5.1j Predicted probabilities of unemployment to inactivity transitions by duration of unemployment



Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

Figure 5.1j shows that those who had been unemployed for more than 12 months have higher predicted probabilities to transition to inactivity than those who had been unemployed for less than 12 months. The four predicted probabilities reported in each panel are also very similar. The coefficients of long-term unemployment reported in columns 6, 7 and 8 of the non-searching models were statistically significant at 10%, while the Wald statistics for the non-searching models showed that the models' coefficients were jointly statistically significant, but the Wald statistics for the searching models' coefficients were not jointly significant.

5.3 Multinomial unemployment transitions results

In this section I present and discuss the results of the multinomial unemployment transition models (unemployment to employment or to inactivity), estimated separately for the searching and non-searching unemployed, with and without unemployment duration. In order to facilitate the interpretation of the results, I also estimated the predicted probabilities of these transitions at various levels of explanatory variables like the reservation wage, age, level of education and gender.

Table 5.2a presents the results of the multinomial unemployment transitions of the searching unemployed, for models that exclude long-term unemployment as explanatory variable. The low p-values of the Wald statistics for all of these models show that the coefficients of the explanatory variables are jointly statistically significant at the 1%level.

Table 5.2a: Multinomial logit (MNL) and multinomial probit (MNP) estimates of multinomial unemployment transitions, searching unemployment.

	1		2		3		4	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Reservation wage*1000	**0.06**	0.02	**0.05**	0.01	**0.06**	0.02	**0.05**	0.01
Gender	***0.44***	**-0.34**	***0.36***	***-0.27***	***0.48***	**-0.32**	***0.39***	***-0.26***
Age	***0.02***	***0.02***	***0.02***	***0.02***	***0.02***	***0.02***	***0.02***	***0.02***
Education: Incomplete Primary	-0.47	**-0.95**	-0.32	**0.73**	-0.49	**-0.96**	-0.33	**-0.72**
Education: Complete Primary	-0.28	***-1.44***	-0.16	***-1.13***	-0.31	***-1.45***	-0.18	***-1.13***
Education: Incomplete Secondary	-0.47	***-1.42***	-0.31	***-1.09***	-0.49	***-1.42***	-0.32	***-1.09***
Education: Complete Secondary	-0.06	**-1.11**	0.01	***-0.86***	-0.07	**-1.11**	0.01	***-0.85***
Education: Post-secondary	0.07	**-1.16**	0.12	***-0.91***	0.07	**-1.16**	0.13	***-0.90***
Race: Asian/Indian	-0.87	-1.27	-0.72	-1.09	-0.71	-1.19	-0.59	-1.02
Race: African	-0.06	-0.69	-0.08	-0.59	0.04	-0.64	0.01	-0.55
Race: Coloured	0.26	0.05	0.14	-0.01	0.36	0.11	0.22	0.03
Marital Status	-0.20	*-0.30*	-0.15	*-0.22*	-0.17	*-0.28*	-0.13	*-0.21*
Per capita income*1000	0.04	0.01	0.03	0.004	0.06	0.02	0.05	0.01
Urban	*0.27*	0.20	*0.21*	0.14	*0.27*	0.20	*0.21*	0.14
HH size	-0.02	0.01	-0.01	0.01	-0.02	0.01	-0.01	0.01
HH grant	*-0.24*	-0.11	*-0.19*	-0.08	-	-	-	-
HH pension	-	-	-	-	-0.21	-0.13	-0.17	-0.10
HH child	-	-	-	-	0.04	-0.01	0.32	-0.01
N	2017		2017		2017		2017	
Pseudo R2	0.05				0.05			
Wald	206.35		215.19		205.74		214.39	
P(wald)	***0.00***		***0.00***		***0.00***		***0.00***	

Notes: (1) = MNL, uen (unemployed-employed-not active), HH grant, (2) = MNP, uen, HH grant, (3) = MNL, uen, HH pension and HH child grant; (4) = MNP, uen, HH pension and HH child grant. (a) = uen = 1 (employed); (b) = uen = 2 (not active). Robust standard errors were used to obtain test statistics; ***bold italic***, **bold**, *italic* denote p-values less than 0.01, 0.05 and 0.1, respectively. All estimated equations include provincial dummies.

The reservation wage coefficients are positive for all the transitions, which indicates that the unemployed with higher reservation wages are more likely to transition to employment or to inactivity relative to remaining unemployed. However, only the coefficients of the transitions to employment were statistically significant at conventional levels.

The coefficients on gender are positive for transitions to employment, which shows that men are more likely to transition to employment, relative to remaining unemployed. The coefficients are also statistically significant at the 1% level. The negative coefficients on gender for transitions to inactivity show that women are more likely than men to transition to inactivity, relative to remaining unemployed. These coefficients are also statistically significant at the 5% level.

The coefficients for age are positive for all transitions, which means that older workers are more likely to transition to either employment or to inactivity, relative to remaining unemployed. All of the coefficients on age are statistically significant at the 1% level.

For the transitions to employment, the coefficients on level of education are all negative, except for post-secondary education. This means that relative to no schooling, the unemployed with any level of schooling, except post-secondary education, are less likely to transition to employment, relative to remaining unemployed. Unemployed people with a post-secondary education are the only ones who are more likely to transition to employment, rather than to remain unemployed, than people with no schooling. However, none of these coefficients are statistically significant at conventional levels.

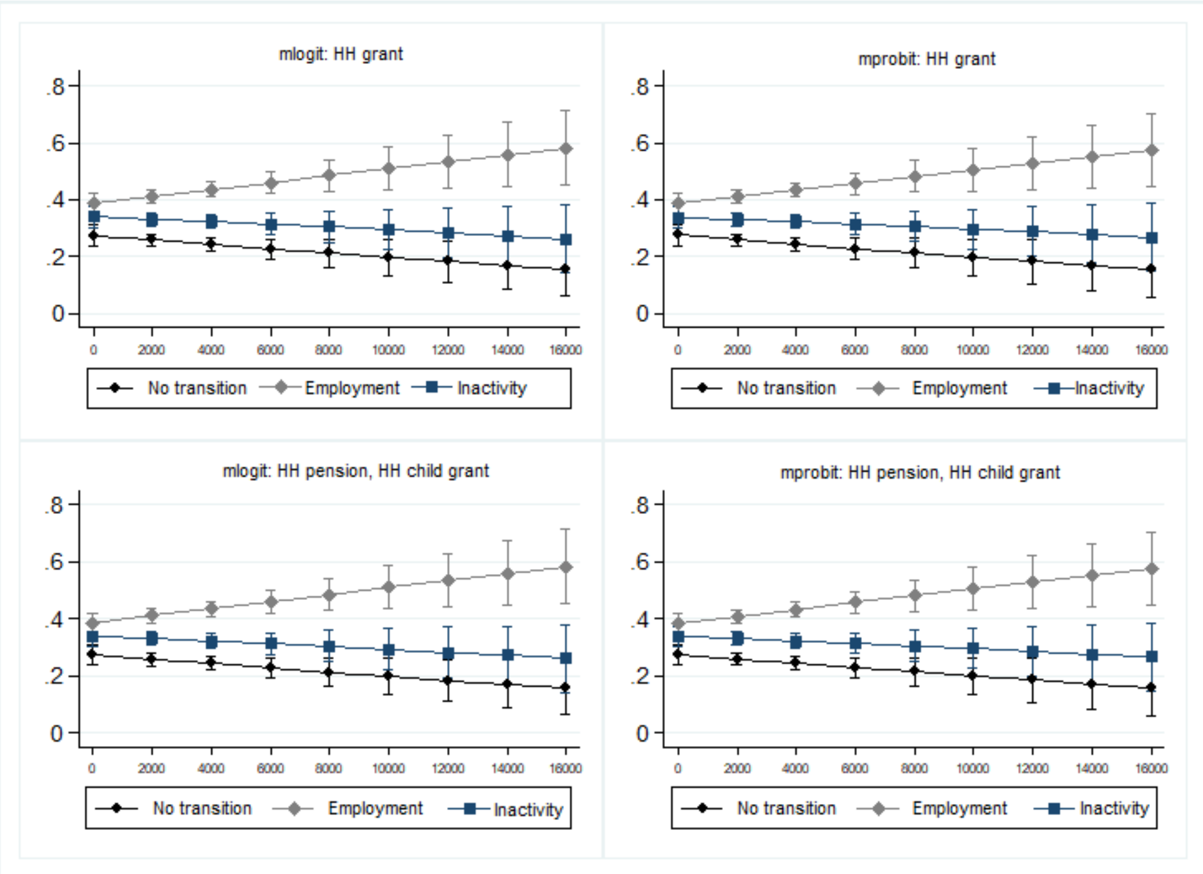
All the education coefficients are negative for the transitions to inactivity, which means that unemployed people with any level of schooling are less likely to transition to inactivity, relative to remaining unemployed, than people with no schooling. These coefficients are all statistically significant at conventional levels.

The marital status coefficients for transitions to inactivity are negative and statistically significant at 10%. This means that people who were not married or living with partners are less likely to transition to inactivity, relative to remaining unemployed, than people who were married or living with partners. The coefficients on urban are positive for transitions to employment, and are statistically significant at the 10% level. This indicates that people residing in urban areas are more likely to transition to employment, relative to remaining unemployed, than people residing in rural areas. Furthermore, the coefficients on household receipt of income from a government grant are negative for transitions to employment, and are statistically significant at the 10% level, which indicates that unemployed people residing in a household that receive income from a government grant are less likely to transition to employment, relative to remaining unemployed, than people residing in households that did not receive income from a government grant.

Figures 5.2a-d below present predicted transition probabilities for multinomial logit and probit unemployment transition models, for those who are searching unemployed, for models that exclude unemployment duration, over different levels of the reservation wage, gender, age, and the level of educational attainment. The top panels show the predicted probabilities for models that included a household grant receipt dummy, while the bottom panels show the predicted probabilities for models that included separate dummy variables for household receipt of the government old-age pension and the child support grant. The left-hand side panels show predicted probabilities for multinomial logit models, while the right-hand side panels show predicted probabilities for multinomial probit models.

Figure 5.2a shows the predicted probabilities of unemployment transitions for different values of the reservation wage, for those that are searching unemployed.

Figure 5.2a Predicted probabilities of unemployment transitions by reservation wage

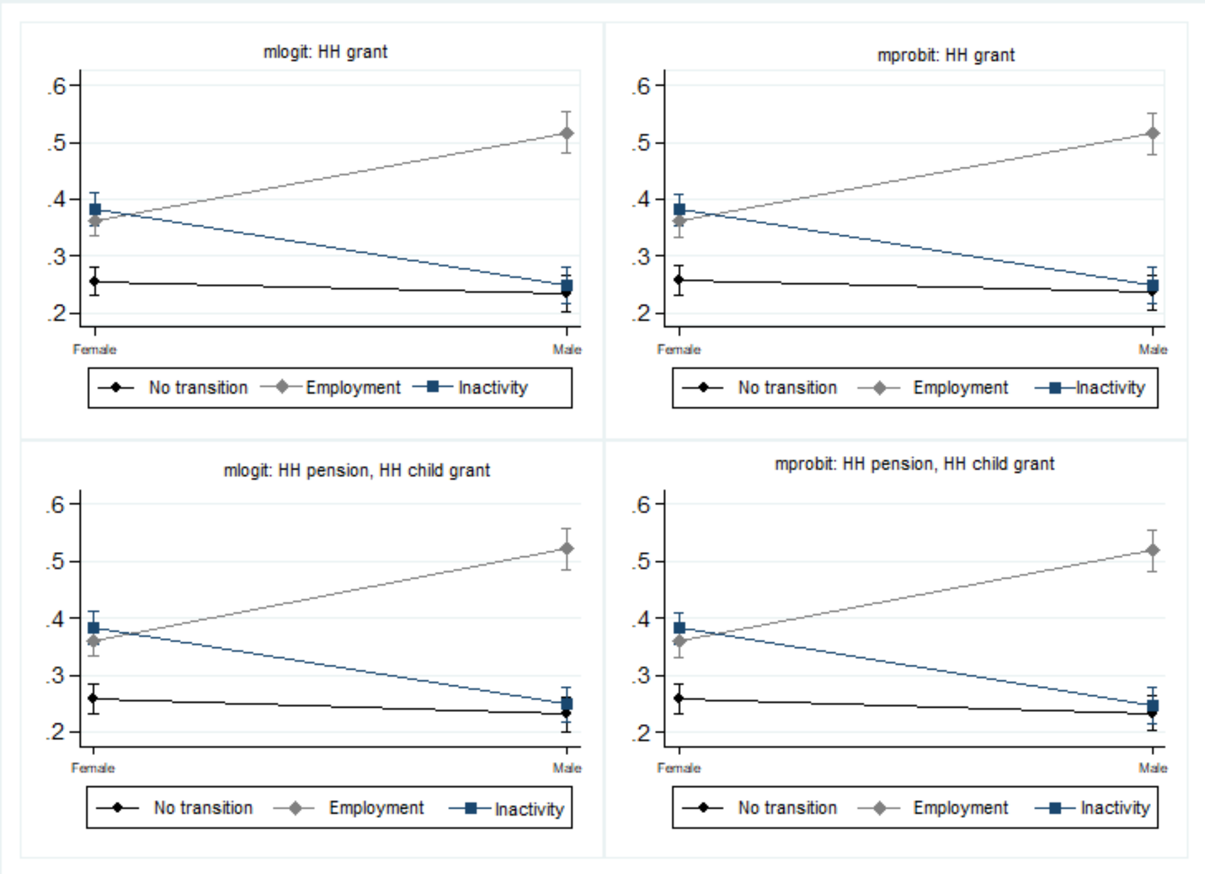


Source: NIDS W3 and W4 data. Author's own calculations.

In all four models, the predicted employment transition probability increases as the reservation wage increases, whereas the predicted probabilities for remaining unemployment and transitioning to inactivity decreases as the reservation wage increases. The predicted probabilities for each type of transition are similar across the four models, and display very similar patterns over the values of the reservation wage.

Figure 5.2b shows the predicted unemployment transition probabilities for searching unemployed men and women.

Figure 5.2b Predicted probabilities of unemployment transitions by gender

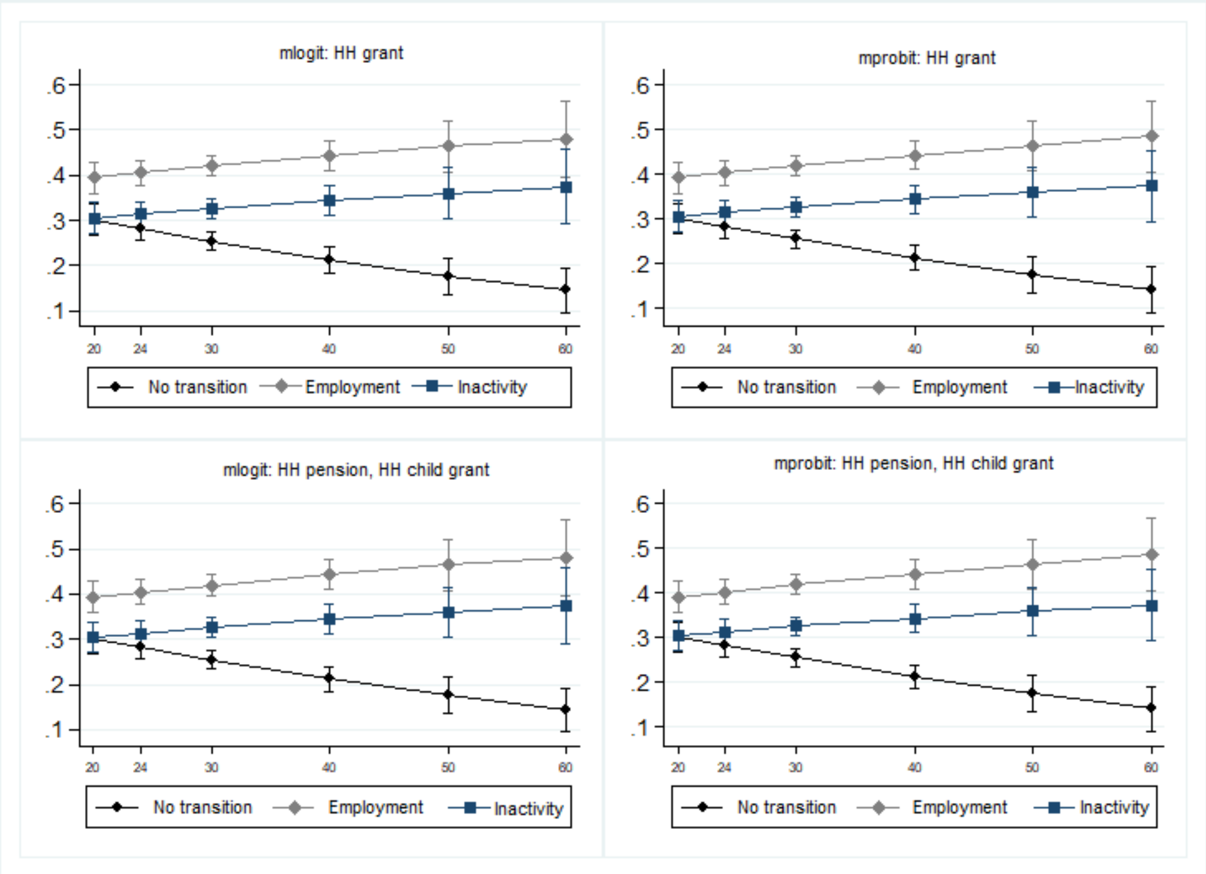


Source: NIDS W3 and W4 data. Author's own calculations.

Women have lower predicted probabilities to transition to employment than men, while they have higher predicted probabilities to transition to inactivity, as well as slightly higher predicted probabilities to remain unemploymed. For women, there is only a slight difference in the predicted probabilities of transitioning to employment and transitioning to inactivity. Men, however, have much higher predicted probabilities to transition to employment than to transition to inactivity or to remaining unemployed. The predicted probabilities are similar across the four models, and display very similar patterns.

Figure 5.2c shows the predicted probabilities for the unemployment transitions over different ages, for the searching unemployed.

Figure 5.2c Predicted probabilities of unemployment transitions by age

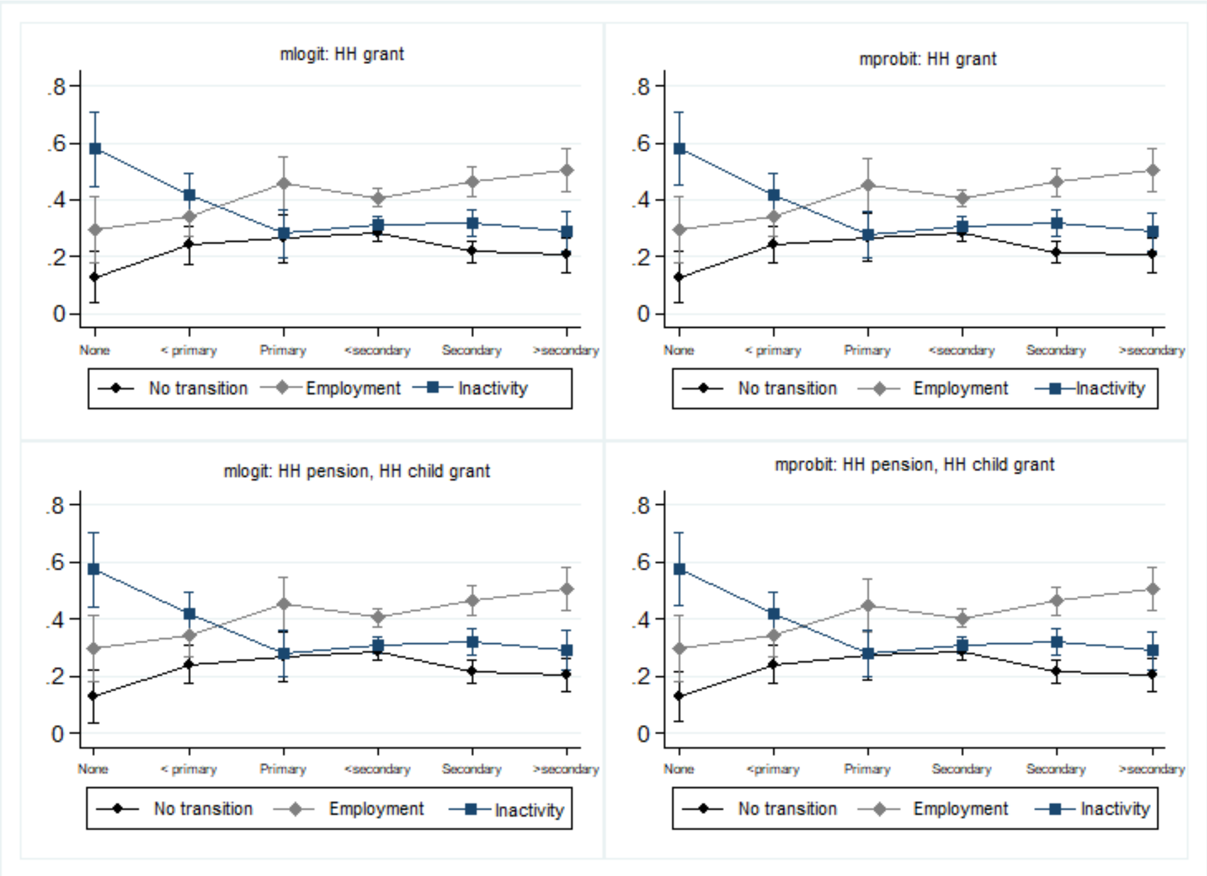


Source: NIDS W3 and W4 data. Author's own calculations.

As age increases, so do the predicted probabilities of transitioning to employment and to inactivity. The predicted probabilities of remaining unemployed decrease as age increases. Across all ages, workers have higher predicted probabilities of transitioning to employment than transitioning to inactivity or remaining unemployed. For young workers, the difference between the predicted probabilities of transitioning to inactivity or remaining unemployed are very small. This difference increases as age increases: old workers have very low predicted probabilities of remaining unemployed.

Figure 5.2d shows the predicted probabilities of the unemployment transitions over different levels of educational attainment, for the searching unemployed.

Figure 5.2d Predicted probabilities of unemployment transitions by level of education



Source: NIDS W3 and W4 data. Author’s own calculations.

The predicted probabilities of transitioning to employment generally increase as the level of education increases. These higher predicted probabilities are particularly pronounced for those who completed primary education. The predicted probabilities of transitioning to inactivity generally decrease with increased educational attainment. The lower predicted probabilities are also particularly pronounced for those who completed primary education. The predicted probabilities of remaining unemployed increase up to having an incomplete secondary education, whereafter it decreases for completed secondary and post-secondary education. Those with no schooling have much higher predicted inactivity transition probabilities than employment transition probabilities, while those with a post-secondary education have higher predicted employment transition probabilities than inactivity transition probabilities and probabilities of remaining unemployed. Furthermore, the predicted probabilities are similar across the four models, and display very similar patterns over the different levels of educational attainment.

Table 5.2b presents the results of the multinomial unemployment transitions of the non-searching unemployed, for models that exclude long-term unemployment as explanatory variable. The low p-values of the Wald statistics for all these models show that the coefficients on the explanatory variables are jointly significant at the 1% level.

Table 5.2b: Multinomial logit (MNL) and multinomial probit (MNP) estimates of multinomial unemployment transitions, non-searching unemployment.

	1		2		3		4	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Reservation Wage*1000	**0.06**	0.04	**0.05**	0.03	**0.06**	0.04	**0.05**	0.03
Gender	***0.48***	**-0.30**	***0.39***	**-0.23**	***0.51***	**-0.29**	***0.42***	**-0.23**
Age	***0.02***	***0.03***	***0.01***	***0.02***	***0.02***	***0.03***	***0.02***	***0.02***
Education: Incomplete Primary	-0.47	**-0.81**	-0.33	**-0.61**	-0.50	**-0.81**	-0.34	**-0.61**
Education: Complete Primary	-0.40	***-1.30***	-0.27	***-1.01***	-0.44	***-1.29***	-0.30	***-1.01***
Education: Incomplete Secondary	-0.38	***-1.20***	-0.25	***-0.93***	-0.40	***-1.19***	-0.26	***-0.92***
Education: Complete Secondary	-0.09	***-1.08***	-0.03	***-0.84***	-0.11	***-1.08***	-0.03	***-0.83***
Education: Post-secondary	0.16	**-1.01**	0.19	***-0.79***	0.15	-1.01	0.18	***-0.79***
Race: Asian/Indian	-0.94	-1.11	-0.74	-0.92	-0.87	-1.10	-0.69	-0.91
Race: African	-0.34	-0.48	-0.27	-0.39	-0.33	-0.47	-0.25	-0.38
Race: Coloured	-0.20	0.01	-0.16	0.001	-0.17	0.02	-0.14	0.01
Marital Status	-0.17	-0.16	-0.13	-0.12	-0.14	-0.16	-0.11	-0.11
Per capita income*1000	0.07	0.06	0.05	0.05	0.08	0.06	*0.06*	0.05
Urban	0.14	0.02	0.11	0.005	0.14	0.02	0.11	0.003
HH size	-0.01	0.01	-0.01	0.003	-0.02	0.004	-0.01	0.003
HH grant	-0.13	0.10	-0.10	0.09	-	-	-	-
HH pension	-	-	-	-	-0.17	0.02	-0.13	0.01
HH child	-	-	-	-	0.07	0.07	0.06	0.06
N	2349		2349		2349		2349	
Pseudo R2	0.05				0.05			
Wald	244.07		252.39		243.71		251.92	
P(wald)	***0.00***		***0.00***		***0.00***		***0.00***	

Notes: (1) = MNL, uen (unemployed-employed-not active) broad, HH grant, (2) = MNP, uen broad, HH grant, (3) = MNL, uen broad, HH pension and HH child grant; (4) = MNP, uen broad, HH pension and HH child grant. (a) = uen = 1 (employed); (b) = uen = 2 (not active). Robust standard errors were used to obtain test statistics; ***bold italic***, **bold**, *italic* denote p-values less than 0.01, 0.05 and 0.1, respectively. All estimated equations include provincial dummies.

The coefficients for the reservation wage are positive for both transitions, which indicates that those with higher reservation wages are more likely to transition to employment or to inactivity, relative to remaining unemployed. However, only the coefficients of the transitions to employment are statistically significant (at the 5% level).

The gender coefficients are positive for transitions to employment, which are statistically significant at the 1% level of significance. This indicates that men are more likely than women to transition to employment, relative to remaining unemployed. For transitions to inactivity, the gender coefficients are negative, which indicates that women are more likely than men to transition to inactivity, relative to remaining unemployed. These coefficients are also statistically significant at the 5% level.

For transitions to employment and inactivity, the coefficients on age are positive, indicating that older workers are more likely to transition to either employment or to inactivity, relative to remaining unemployed. All these coefficients are statistically significant at the 1% level.

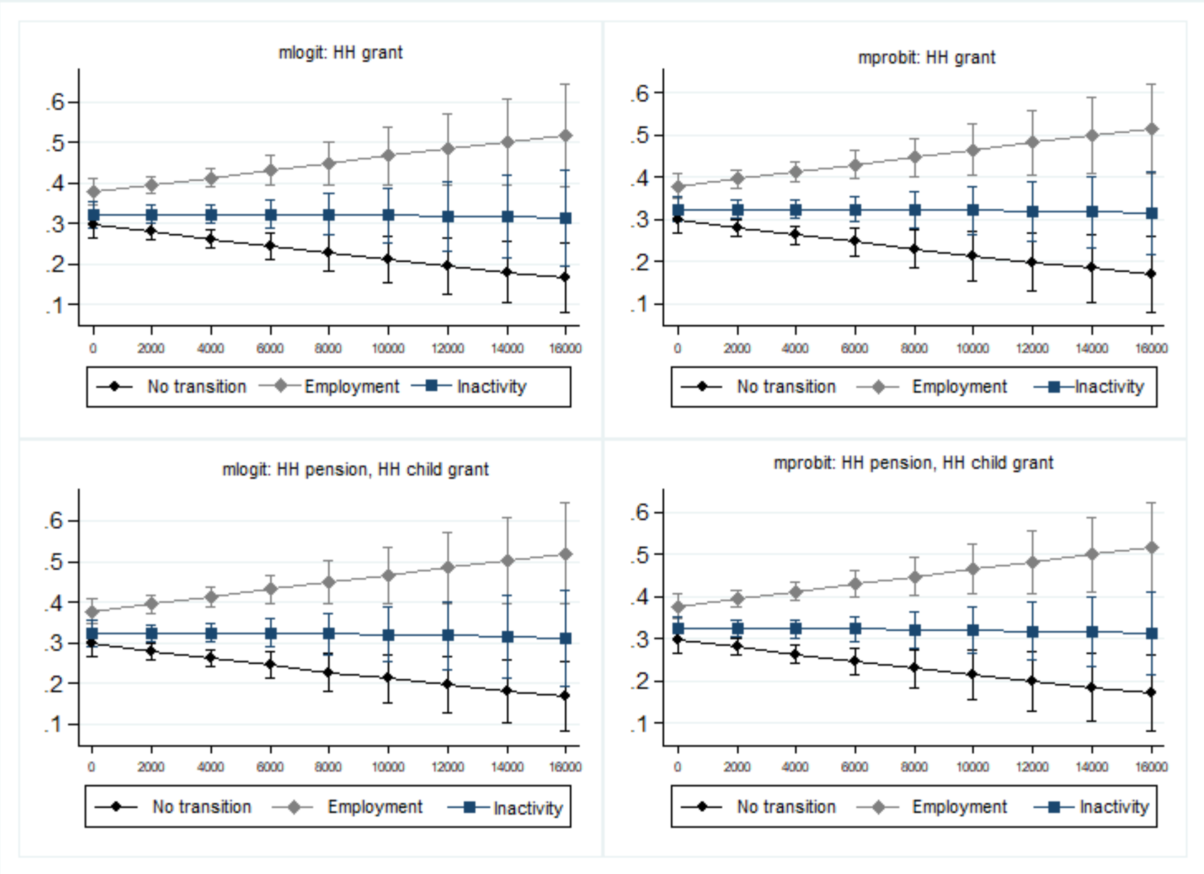
For transitions to employment, the coefficients from incomplete primary to complete secondary are negative, while they are positive for post-secondary education. None of the education coefficients were statistically significant at conventional levels for transitions to employment. This indicates that relative to no schooling, people with an incomplete primary to complete secondary education were less likely to transition to employment relative to remaining unemployed. Also, people with a post-secondary education were more likely to transition to employment relative to remaining unemployed, than people with no schooling. For the transitions to inactivity, all the education coefficients were negative and statistically significant at conventional levels, which indicates that all levels of educational attainment were less likely to transition to inactivity relative to remaining unemployed, than people with no schooling.

The coefficient for income per capita is positive and statistically significant at the 10% level for the multinomial probit that included separate household old-age and child grant receipt dummies. This indicates that unemployed people residing in high income households are more likely to transition to employment, relative to remaining unemployed. The coefficients for the transition to inactivity were not statistically significant.

Figures 5.2e-h below present predicted transition probabilities for multinomial logit and probit unemployment transition models, for those who are non-searching unemployed, for models that exclude unemployment duration, over different levels of the reservation wage, gender, age, and the level of educational attainment. The top panels show the predicted probabilities for models that included a household grant receipt dummy, while the bottom panels show the predicted probabilities for models that included separate dummy variables for household receipt of the government old-age pension and the child support grant. The left-hand side panels show predicted probabilities for multinomial logit models, while the right-hand side panels show predicted probabilities for multinomial probit models.

Figure 5.2e shows the predicted probabilities of the unemployment transitions for different levels of the reservation wage for the non-searching unemployed.

Figure 5.2e Predicted probabilities of unemployment transitions by reservation wage

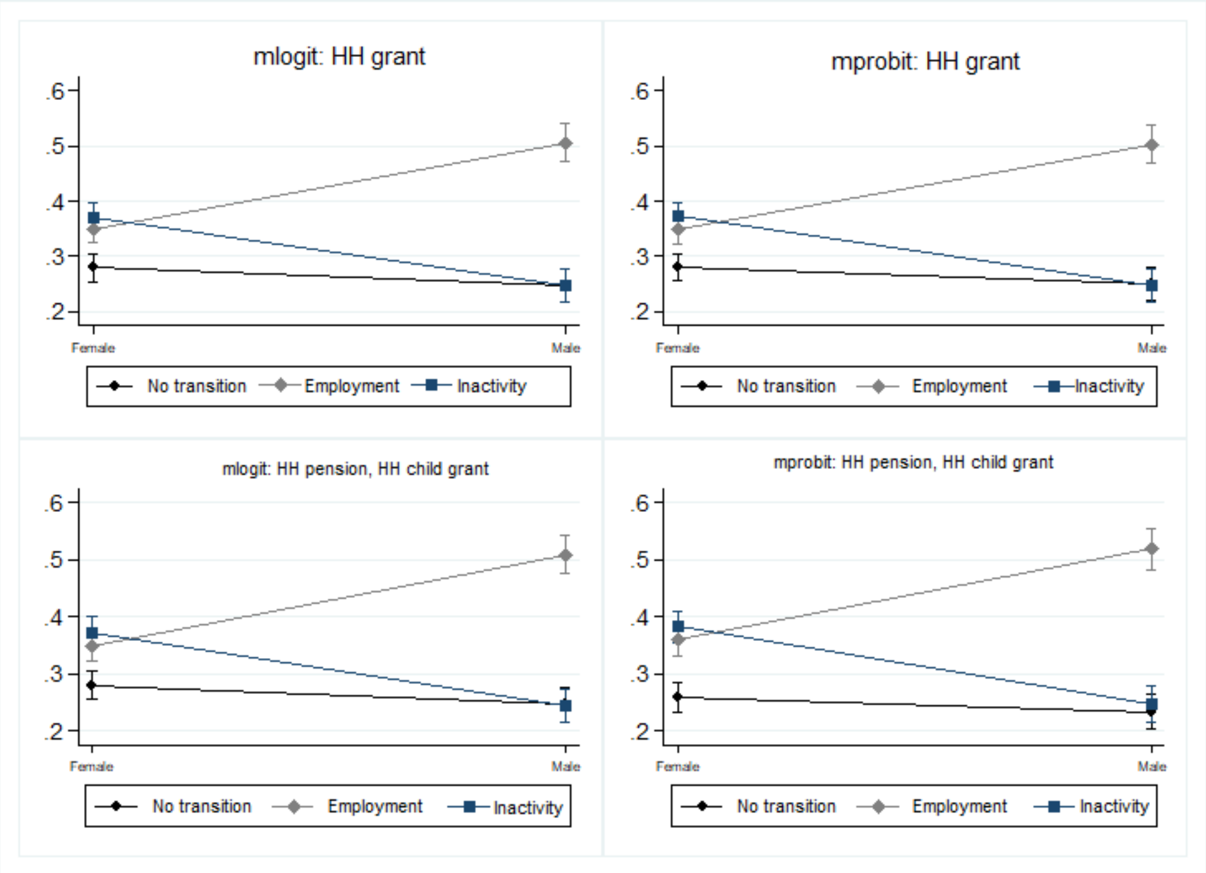


Source: NIDS W3 and W4 data. Author's own calculations.

As the reservation wage increases, the predicted employment transition probabilities increase, while the predicted inactivity transition probabilities decrease slightly, and the predicted probabilities of remaining unemployed decrease more substantially. The predicted probabilities of transitioning to employment are greater than the predicted probabilities of transitioning to inactivity, as well as the predicted probabilities of remaining unemployed. These differences increase as the reservation wage increases. The predicted probabilities for these four models are similar, and they exhibit very similar patterns over the values of the reservation wage.

Error! Reference source not found. shows the predicted unemployment transition probabilities for non-searching unemployed men and women.

Figure 5.2f Predicted probabilities of unemployment transitions by gender

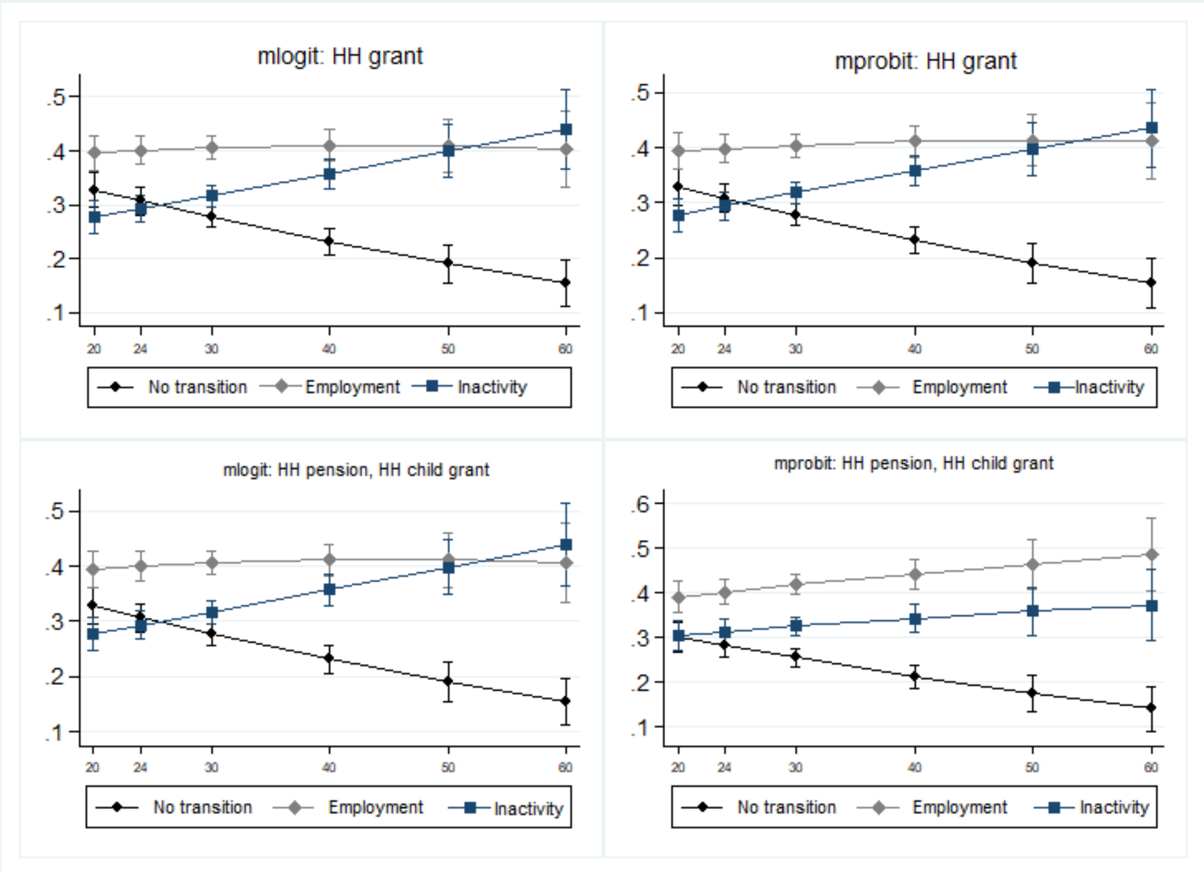


Source: NIDS W3 and W4 data. Author's own calculations.

Women have higher predicted probabilities to transition to inactivity than men, lower predicted probabilities to transition to employment, and slightly higher predicted probabilities to remain unemployed. Furthermore, women have slightly higher predicted probabilities to transition to inactivity than to transition to employment. Men, however, have much higher predicted probabilities to transition to employment than to inactivity or to remaining unemployed. The predicted probabilities for all four models are similar, and display very similar patterns.

Figure 5.2g shows the predicted unemployment transition probabilities for different ages for the non-searching unemployed.

Figure 5.2g Predicted probabilities of unemployment transitions by age



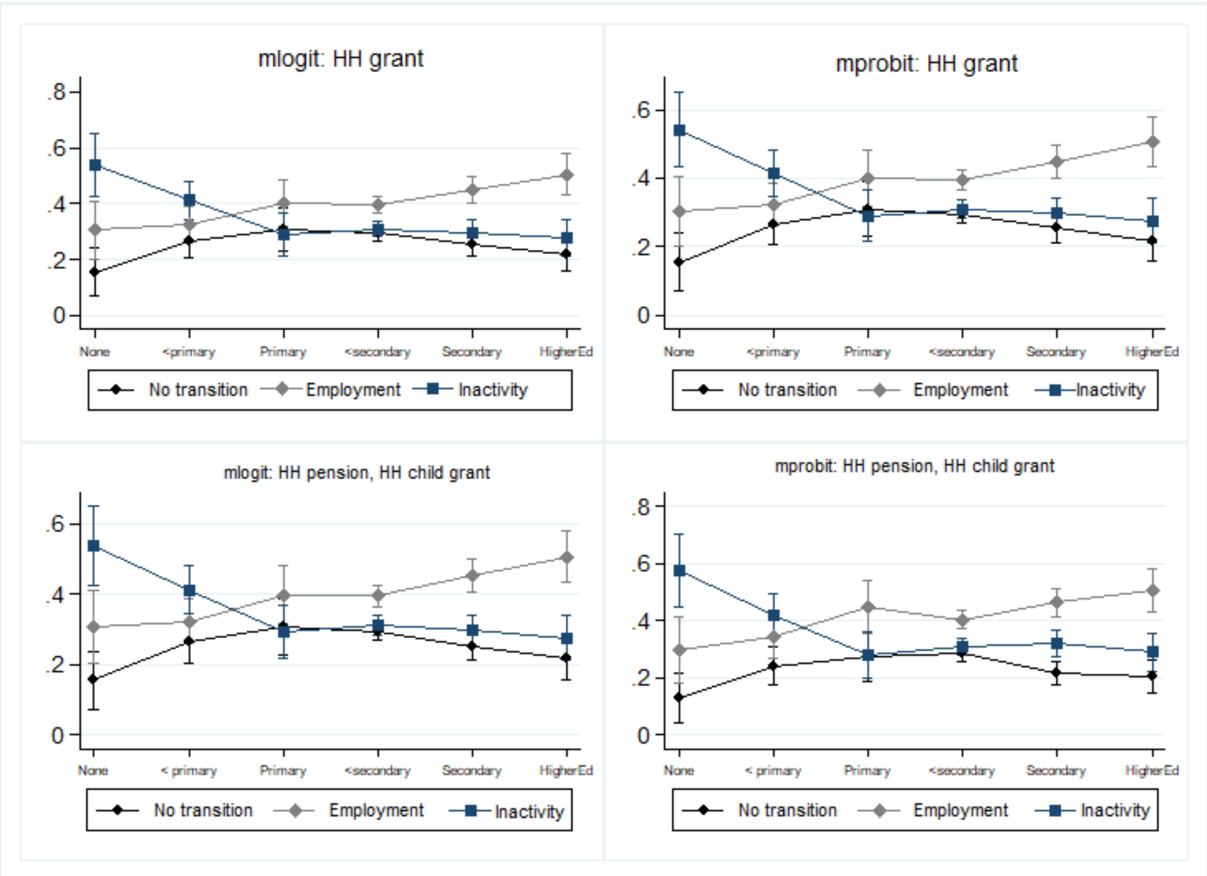
Source: NIDS W3 and W4 data. Author's own calculations.

The predicted probabilities for transitioning to employment are relatively flat across all ages in three of the models, with the exception of the multinomial probit model that includes the household pension and child grant receipt dummies. For this model, the predicted employment transition probabilities increase slightly with age. The predicted inactivity transition probabilities increase with age, while the predicted probabilities of remaining unemployed decrease with age.

Younger people have higher predicted probabilities of remaining unemployed, rather than transitioning to inactivity, except in the multinomial probit with the household pension and child grant receipt dummies. Older people have higher predicted inactivity transition probabilities than employment transition probabilities (except in the multinomial probit with the household pension and child grant receipt dummies) or to remain unemployed.

Figure 5.2h shows the predicted probabilities of unemployment transitions for different levels of education for the non-searching unemployed.

Figure 5.2h Predicted probabilities of unemployment transitions by level of education



Source: NIDS W3 and W4 data. Author's own calculations.

The predicted employment transition probabilities generally increase as the level of education increases. The increased predicted probabilities are pronounced for those with complete primary, as well as for those with post-secondary education. The predicted inactivity transition probabilities generally decrease as educational attainment increases. The decreased predicted probabilities are particularly pronounced for those with complete primary education. The predicted probabilities of remaining unemployed increase up to completed primary education, whereafter they decrease for incomplete and complete secondary education, as well as for post-secondary education (except in the multinomial probit model that includes the separate household pension and child support grant receipt dummies).

Table 5.2c shows the results of the multinomial unemployment transition models for the searching unemployed, in models that include unemployment duration as explanatory variable. As discussed previously, when unemployment duration is included, the number of observations decreases significantly. The low p-values of the Wald statistics indicate that the coefficients of the explanatory variables of the multinomial probit models are jointly statistically significant at conventional levels.

Table 5.2c: Multinomial logit (MNL) and multinomial probit (MNP) estimates of multinomial unemployment transitions, searching unemployment, with unemployment duration

	1		2		3		4	
	(a)	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**	**(a)**	**(b)**
Reservation Wage*1000	0.03	-0.04	0.03	-0.02	0.03	-0.05	0.02	-0.02
Long-term unemployment	-0.35	0.51	-0.25	0.44	-0.49	0.54	-0.38	0.45
Gender	0.63	-0.07	0.49	-0.12	0.51	-0.13	0.38	-0.17
Age	0.02	0.01	0.01	0.01	0.02	0.01	0.01	0.01
Education: Incomplete Primary	*-2.33*	*-2.27*	**-1.67**	**-1.66**	-2.02	*-2.26*	*-1.48*	**-1.68**
Education: Complete Primary	0.02	-2.65	0.03	**-2.12**	0.09	-2.65	0.12	**-2.07**
Education: Incomplete Secondary	-1.33	-1.86	-0.87	*-1.33*	-1.12	-1.83	-0.72	*-1.33*
Education: Complete Secondary	-1.03	*-2.66*	-0.64	**-1.95**	-0.80	-2.68	-0.48	**-1.97**
Education: Post-secondary	-0.89	-1.95	-0.54	-1.40	-0.77	-1.92	-0.45	-1.41
Race: Coloured	0.56	0.24	0.46	0.21	0.78	0.48	0.63	0.39
Marital Status	-0.69	*-1.07*	-0.57	**-0.84**	-0.71	*-1.06*	-0.57	*-0.82*
Per capita income*1000	0.003	0.001	0.01	0.01	-0.05	0.07	-0.03	0.05
Urban	0.04	0.74	0.01	0.54	0.10	0.70	0.01	0.51
HH size	0.02	-0.001	0.02	0.002	0.06	-0.02	0.04	-0.01
HH grant	0.60	0.64	0.43	0.46	-	-	-	-
HH pension	-	-	-	-	-0.27	0.15	-0.23	0.12
HH child	-	-	-	-	-0.10	0.74	-0.12	0.53
N	188		188		188		188	
Pseudo R2	0.13				0.14			
Wald	53.67		62.26		58.04		67.87	
P(wald)	0.20		*0.06*		0.15		**0.03**	

Notes: (1) = MNL, uen (unemployed-employed-not active), HH grant, (2) = MNP, uen, HH grant, (3) = MNL, uen, HH pension and HH child grant; (4) = MNP, uen, HH pension and HH child grant. (a) = uen = 1 (employed); (b) = uen = 2 (not active). Robust standard errors were used to obtain test statistics; ***bold italic***, **bold**, *italic* denote p-values less than 0.01, 0.05 and 0.1, respectively. All estimated equations include provincial dummies.

The coefficients for the reservation wage are positive for all the transitions, which indicates that people with higher reservation wages are more likely to transition to either employment or to inactivity, relative to remaining unemployed. However, none of these coefficients were statistically significant at conventional levels.

For the transitions to employment, the coefficients for long-term unemployment are negative, which indicates that people who were long-term unemployed are less likely to transition to employment than to remain unemployed. The long-term unemployment coefficients for transitions to inactivity are also negative, indicating that people who were long-term unemployed are more likely to transition to inactivity than to remain unemployed. However, none of the long-term unemployment coefficients are statistically significant at conventional levels.

The coefficients on gender are positive for transitions to employment, indicating that men are more likely to transition to employment, relative to remaining unemployed. For the transitions to inactivity, the coefficients on gender are negative, indicating that women are more likely to transition to inactivity, relative to remaining unemployed. However, none of the gender coefficients were statistically significant at conventional levels.

The coefficients for age are positive for all the transitions, indicating that older workers are more likely to transition to employment or to inactivity, relative to remaining unemployed. However, none of the age coefficients are statistically significant at conventional levels.

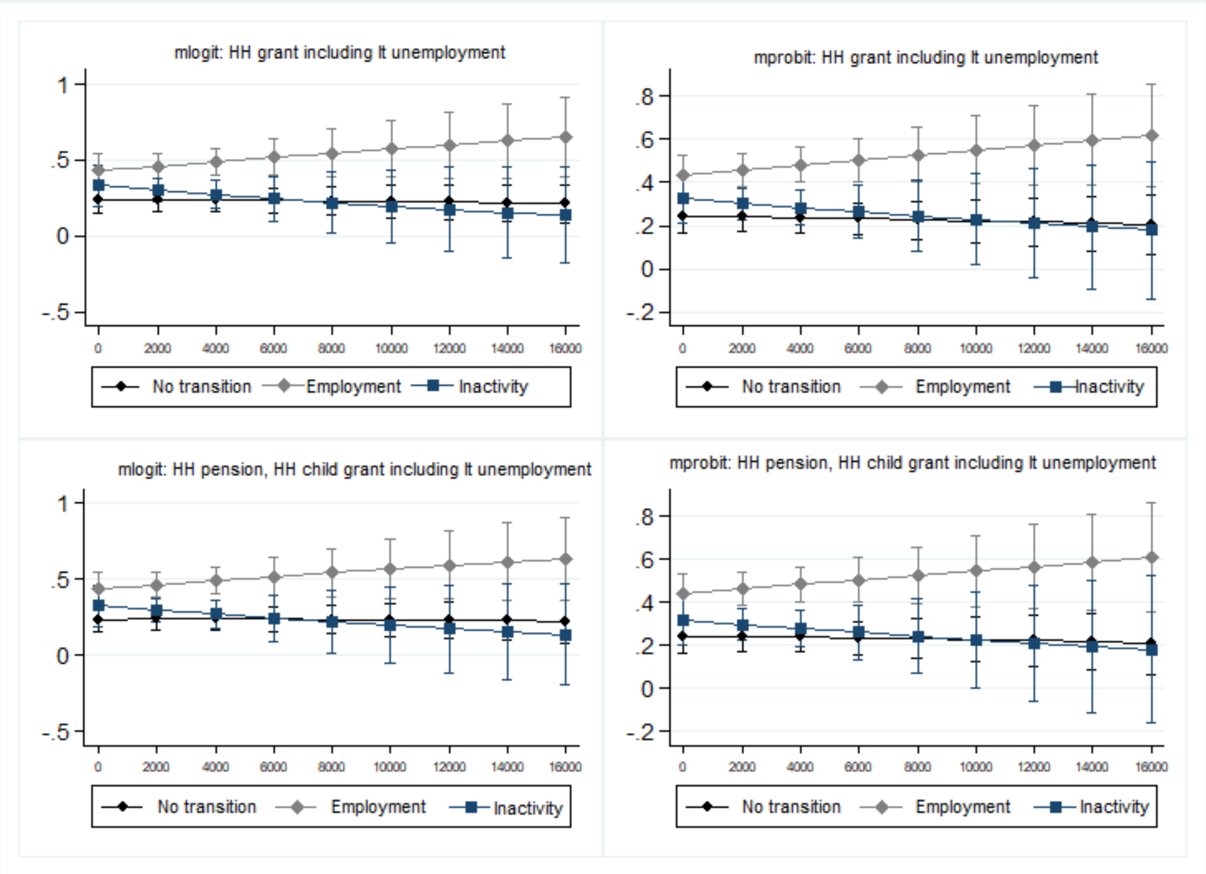
For transitions to employment, the coefficients for complete primary education are positive: people with a complete primary education are more likely to transition to employment, relative to remaining unemployed, than people with no schooling. These coefficients are also statistically significant at conventional levels, except for the multinomial logit model that includes separate dummies for household pension and child support grant receipt. The coefficients on all of the other educational attainment levels are negative: people with levels of educational attainment that differ from complete primary are less likely to transition to employment than people with no schooling, relative to remaining unemployed. Furthermore, for transitions to inactivity, in all four models, those with some schooling are less likely to transition to inactivity than those with no schooling.

The marital status coefficients for transitions to inactivity are negative and statistically significant at conventional levels: people who were not married or living with a partner are less likely to transition to inactivity, relative to remaining unemployed.

Figures 5.2i-m below present predicted transition probabilities for multinomial logit and probit unemployment transition models, for those who are searching unemployed, for models that include unemployment duration, over different levels of the reservation wage, unemployment duration, gender, age, and the level of educational attainment. The top panels show the predicted probabilities for models that included a household grant receipt dummy, while the bottom panels show the predicted probabilities for models that included separate dummy variables for household receipt of the government old-age pension and the child support grant. The left-hand side panels show predicted probabilities for multinomial logit models, while the right-hand side panels show predicted probabilities for multinomial probit models.

Figure 5.2i shows the predicted unemployment transition probabilities for the searching unemployed, over different levels of the reservation wage, in models that included unemployment duration.

Figure 5.2i Predicted probabilities of unemployment transitions by reservation wages

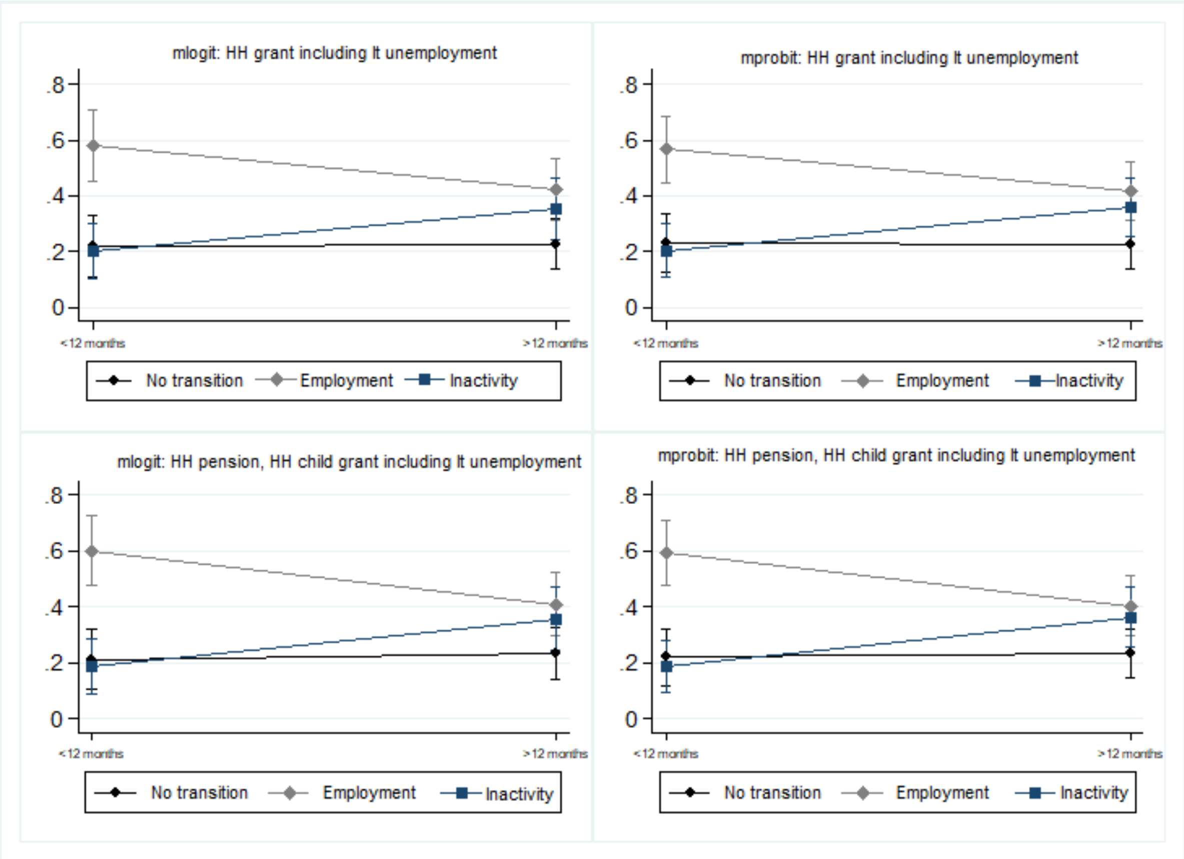


Source: NIDS W3 and W4 data. Author's own calculations.

As the reservation wage increases, the predicted employment transition probabilities increase, while the predicted inactivity transition probabilities decrease. Furthermore, the predicted probabilities of remaining unemployed decrease marginally as the reservation wage increases. At low reservation wages, the predicted inactivity transition probabilities are greater than the predicted probabilities of remaining in unemployment (and vice versa at high reservation wages).

Figure 5.2j shows the predicted unemployment transition probabilities for the searching unemployed, by duration of unemployment.

Figure 5.2j Predicted probabilities of unemployment transitions by long-term unemployment

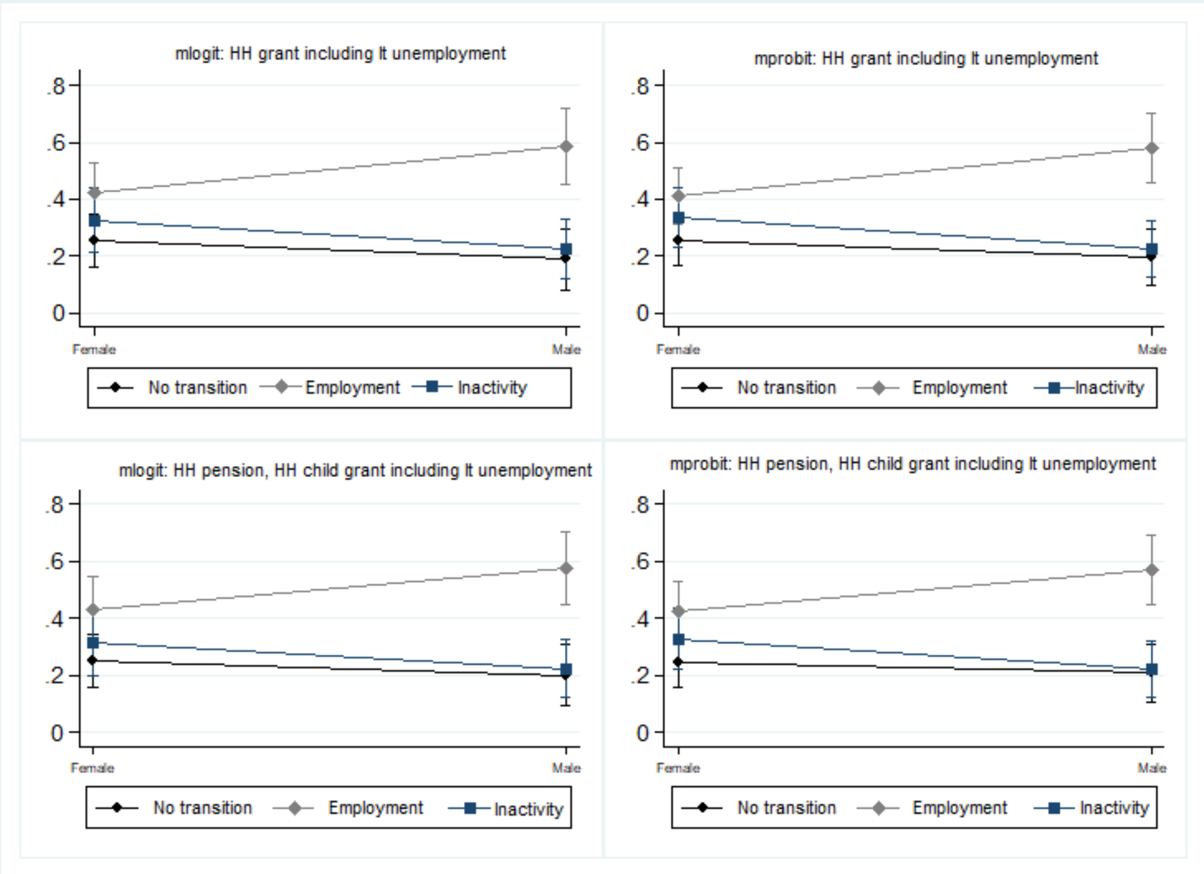


Source: NIDS W3 and W4 data. Author's own calculations.

The predicted employment transition probabilities are greater for the short-term unemployed, while the predicted inactivity transition probabilities are greater for the long-term unemployed. The no transition probabilities were very similar for the short- and long-term unemployed. Furthermore, the predicted probabilities of the four models are very similar.

Figure 5.2k shows the predicted unemployment transition probabilities for men and women, for the searching unemployed, in models that include unemployment duration.

Figure 5.2k Predicted probabilities of unemployment transitions by gender

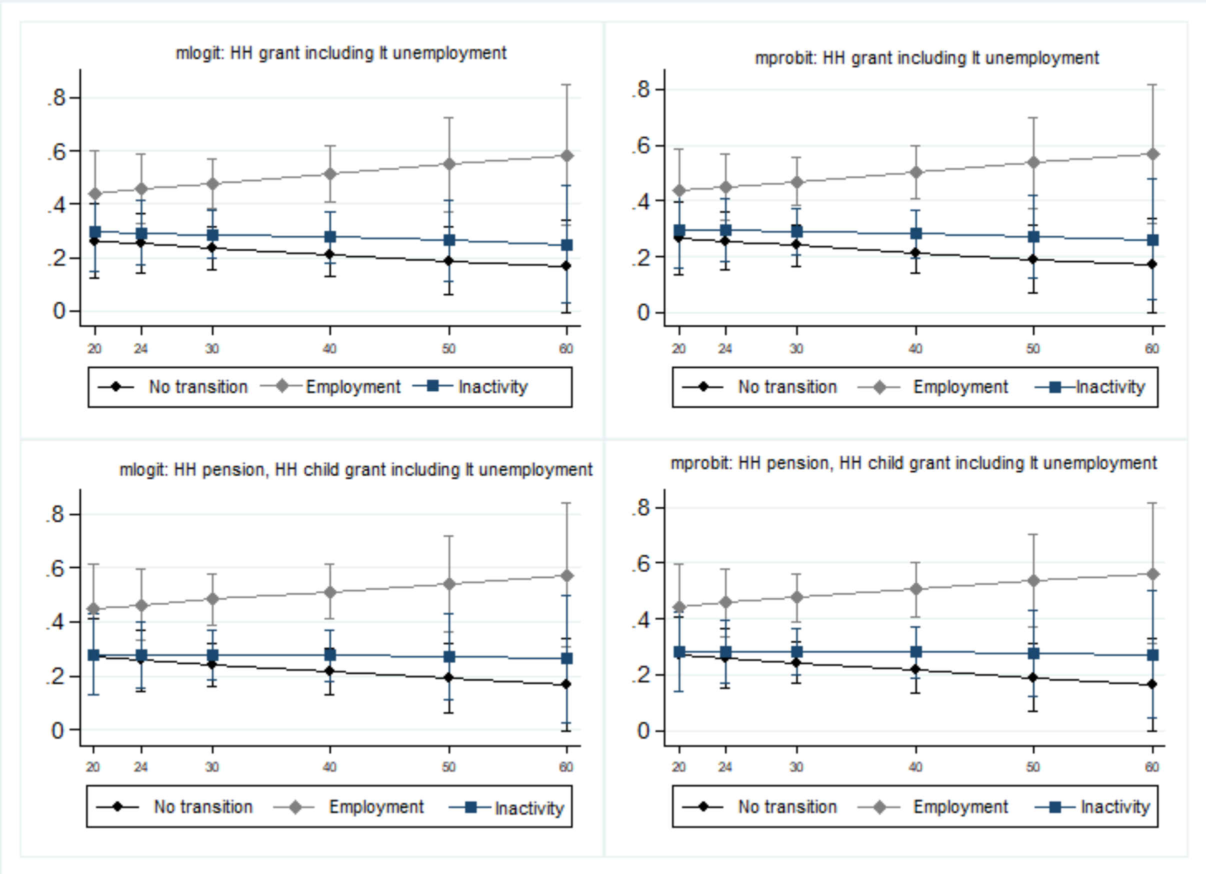


Source: NIDS W3 and W4 data. Author's own calculations.

Men have higher predicted employment transition probabilities, lower predicted inactivity transition probabilities and marginally lower predicted probabilities to remain unemployed. The difference in the predicted transition probabilities is much smaller for women, and the predicted transition probabilities are very similar over the four models.

Figure 5.2k shows the predicted transition probabilities transitions over different ages, for the searching unemployed, in models that included unemployment duration.

Figure 5.2k Predicted probabilities of unemployment transitions by age

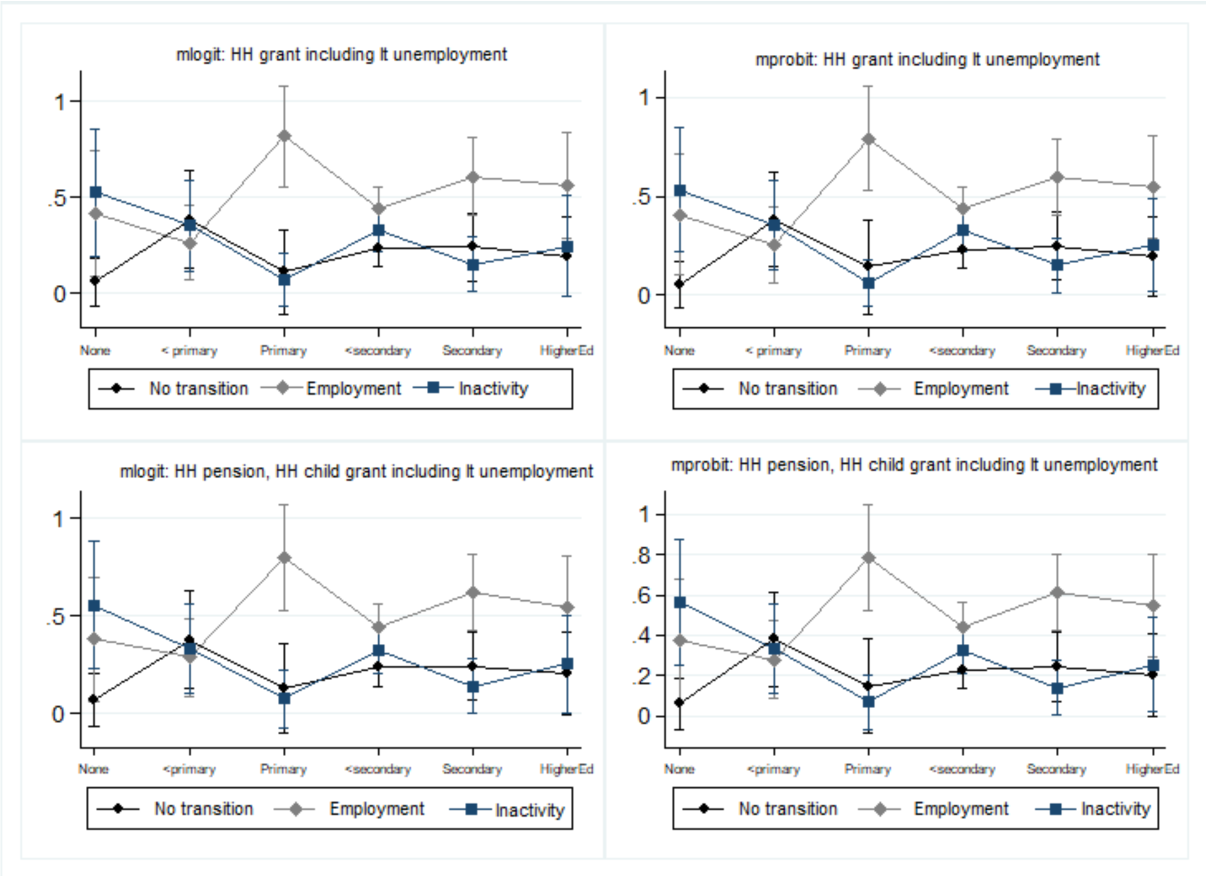


Source: NIDS W3 and W4 data. Author's own calculations.

The predicted employment transition probabilities increase with age, while the predicted inactivity transition probabilities decrease marginally with age. Also, the predicted probabilities to remain unemployed decrease with age. Across all ages, employment transition probabilities are greater than inactivity transition probabilities, while inactivity transition probabilities exceed probabilities of remaining unemployed at almost all ages. The predicted probabilities of the four models are very similar.

Figure 5.2l shows the predicted unemployment transition probabilities of over different levels of educational attainment, for the searching unemployed, in models that include unemployment duration.

Figure 5.2l Predicted probabilities of unemployment transitions by level of education



Source: NIDS W3 and W4 data. Author's own calculations

All three transition probabilities exhibit a non-linear, almost saw-toothed pattern: the employment transition probabilities decrease from no schooling to some primary, before substantially increasing to complete primary, then sharply decreasing to some secondary, before increasing to complete secondary, and decreasing again to post-secondary. The inactivity transition probabilities decrease from no schooling to some primary, and from some primary to complete primary, before increasing to some secondary, decreasing to complete secondary, and finally increasing to post-secondary. Finally, the probabilities of remaining unemployed increase from no schooling to some primary, then decrease to complete primary, increase to incomplete secondary and again to complete secondary, before decreasing to post-secondary.

From complete primary onwards, people with higher levels of educational attainment have higher probabilities to transition to employment than to transition to inactivity or to remain unemployed. Except for no schooling, the predicted probabilities for transitioning to inactivity and for remaining unemployed are very similar across different levels of educational attainment.

People with a complete primary education have the highest predicted employment transition probabilities and the lowest predicted inactivity transition probabilities. People with an incomplete primary education have the lowest predicted employment transition probabilities and the highest predicted probabilities to remain unemployed. Finally, people with no schooling have the highest predicted inactivity transition probabilities. The predicted probabilities of the four models are very similar.

Table 5.2d presents the results of the multinomial unemployment transition models, for the non-searching unemployed, that included the duration of unemployment. Unfortunately, the multinomial probit models could not be estimated, as the likelihood ratios of these models did not converge. Furthermore, the Wald statistics of the two multinomial models could also not be estimated. Therefore, I could not determine if the coefficients of the explanatory variables of these models jointly differed from zero. I therefore decided against presenting and discussing the predicted transition probabilities for these models. They are, however, available on request.

Table 5.2d: Multinomial logit (MNL) estimates of multinomial unemployment transitions, non-searching with unemployment duration

	1		2	
	(a)	**(b)**	**(a)**	**(b)**
Reservation Wage*1000	0.04	0.01	0.04	0.01
Long-term unemployment	-0.32	*0.74*	-0.45	*0.85*
Gender	*0.76*	0.02	0.62	-0.08
Age	-0.001	-0.001	-0.001	-0.004
Education: Incomplete Primary	-1.21	-1.32	-0.97	*-1.38*
Education: Complete Primary	-0.53	***-2.83***	-0.38	***-2.93***
Education: Incomplete Secondary	-0.63	-1.24	-0.41	-1.23
Education: Complete Secondary	-0.39	**-2.28**	-0.16	**-2.34**
Education: Post-secondary	-0.08	-1.29	0.01	-1.38
Race: African	***-14.60***	0.59	***-14.87***	1.27
Race: Coloured	***-13.90***	0.79	***-14.02***	1.58
Marital Status	*-0.75*	**-1.24**	*-0.75*	**-1.21**
Per capita income*1000	0.07	0.19	0.02	0.29
Urban	-0.04	-0.02	-0.001	-0.08
HH size	-0.03	*-0.13*	0.01	**-0.17**
HH grant	*0.77*	**1.12**	-	-
HH pension	-	-	-0.14	0.60
HH child	-	-	-0.15	*1.03*
N	224		224	
Pseudo R2	0.15		0.16	
Wald	.		.	
P(wald)	.		.	

Notes: (1) = MNL, uen (unemployed-employed-not active) broad, HH grant, (2) = MNL, uen broad, HH pension and HH child grant;. (a) = uen = 1 (employed); (b) = uen = 2 (not active). Robust standard errors were used to obtain test statistics; ***bold italic***, **bold**, *italic* denote p-values less than 0.01, 0.05 and 0.1, respectively. All estimated equations include provincial dummies.

The coefficients for reservation wages are positive for all the transitions: people with higher reservation wages are more likely to transition to either employment or to inactivity, relative to remaining unemployed. None of the coefficients are statistically significant at conventional levels, however.

For transitions to employment, the coefficients for long-term unemployment are negative: people who were long-term unemployed are less like to transition to employment, relative to remaining in unemployment. However, the coefficients were not statistically significant. For the transitions to inactivity, the coefficients for long-term unemployment were positive and statistically significant at the 10% level: people who were long-term unemployed are more likely to transition to inactivity, relative to remaining unemployed.

The coefficients on gender are positive for employment transitions: men are therefore more likely to transition to employment, relative to remaining unemployed. The gender coefficient is statistically significant in the multinomial logit that includes the household grant receipt dummy. For the transitions to inactivity, the coefficient on gender is positive in the multinomial logit that includes the household grant receipt dummy, while it is negative in the multinomial logit that includes separate dummies for household receipt of the government old-age pension and the child support grant. However, neither of these coefficients are statistically significant.

The coefficients for age were negative for all transitions: older people are less likely to transition to employment or to inactivity, relative to remaining unemployed. However, none of these coefficients are statistically significant.

For the transitions to employment, the coefficients on education are all negative, except for post-secondary education in the multinomial logit that includes separate dummies for household old-age pension and child support grant receipt.

People with any schooling are therefore less likely than those with no schooling to transition to employment, relative to remaining unemployed, except for post-secondary education). However, none of the coefficients were statistically significant at conventional levels. For transitions to inactivity, all the coefficients on education are negative, which indicates that those with any schooling are less likely than those with no schooling to transition to inactivity, relative to remaining unemployed. The coefficients for complete primary and complete secondary education are statistically significant at conventional levels, as well as the coefficient on incomplete primary (in the multinomial logit that includes the household grant receipt dummy).

The coefficients on race for employment transitions are negative and statistically significant at the 1% level. This means that African or Coloured people are substantially less likely than White people to transition to employment, relative to remaining unemployed.

The coefficients on marital status are negative for both transitions, and are statistically significant at conventional levels. This indicates that people who were not married or living with a partner are less likely to transition to either employment or to inactivity, relative to remaining unemployed. For transitions to inactivity, the coefficients on household size are negative and statistically significant at conventional levels, which indicates that people who form part of larger households are less likely to transition to inactivity, relative to remaining unemployed.

The coefficient for household receipt of income from a grant is positive and statistically significant at conventional levels for transitions to employment and to inactivity. Furthermore, the coefficient for household receipt of a child support grant is positive and statistically significant at the 10% level, which means that people in households in which a child support grant is received, are more likely to transition to inactivity, relative to remaining unemployed.

Across all the estimated models, the predicted probabilities obtained for reservation wages exhibited the same patterns for unemployment to employment and unemployment to inactivity transitions. However, for the no transition cohort, the models that did not include unemployment duration indicated a clear decline in the probability of no transition as the reservation wage increased whereas the models that did include unemployment duration only indicated a marginal decline in the probability of no transition as the reservation wage increased.

Across all the estimated models, the predicted probabilities indicated that women had a higher probability to transition to inactivity and to remain in unemployment (marginally), and a lower predicted probability to transition to employment, than men. Women had a higher predicted probability to transition to inactivity than to transition to employment or to remain unemployment in the models that did not include unemployment duration; in the models that did include unemployment duration, women had a higher predicted probability to transition to employment than to transition to inactivity or to remain unemployed. Men had a higher predicted probability to transition to employment than to transition to inactivity or to remainining unemployed, although the predicted probabilities were very similar.

The predicted probabilities to transition to employment increased with age, while those of remaining unemployed decreased with age in all the estimated models. The predicted probabilities to transition to inactivity increased with age in the models that did not include unemployment duration, and decreased with age in the models that did include unemployment duration. For the models based on the data of the searching unemployed, transitions to employment had the highest predicted probabilities, followed by transitions to inactivity; remaining unemployed had the lowest predicted probabilities. For the non-searching unemployed, younger workers had a higher predicted probability to transition to employment than to make no transition, followed by the predicted probability to transition to inactivity. Older workers had a higher predicted probability to transition to inactivity, followed by the predicted probability to transition to employment, and the lowest predicted probability of no transition.

Overall, the predicted probabilities to transition to employment increased, and to transition to inactivity decreased, with the level of education. The predicted probabilities of no transition were lower for no schooling and a completed primary education, while they were substantially higher for an incomplete primary and incomplete secondary education in the models that included unemployment duration. In the models that did not include unemployment duration, the predicted probabilities of no transition increased up to an incomplete secondary education and thereafter decreased until a post-secondary education. All the estimated predicted probabilities indicated that there was a pronounced effect at a completed primary education: for an education less than an incomplete primary education, the predicted probability to transition to inactivity was the highest, followed by the predicted probability to transition to employment. The lowest predicted probability was for no transition. For a completed primary education and beyond, in the models that did not include unemployment duration, the predicted probability to transition to employment was the highest, followed by the predicted probability to transition to inactivity. The lowest predicted probability was for no transition. For a completed primary education and beyond, in the models that did include unemployment duration, the predicted probability to transition to employment was the highest, followed by the predicted probability of no transition. The lowest predicted probability was for transitions to inactivity.

5.4 Unemployment duration results

In this section I present and discuss the results of the unemployment duration logit and probit regressions that I estimated.

Table 5.3a presents the results of the unemployment duration logit and probit estimates for wave 3 and wave 4. Columns 1 to 4 present the results for the wave 3 duration models, while columns 5 to 8 present the results for the wave 4 duration models. As explained in Chapter 3, I estimated separate duration models for each wave because of the incomplete employment histories collected by NIDS.

As indicated in section 3.5, I estimated duration models with and without the reservation wage, to detect if the reservation wage is endogenous in the duration models. The results of the models estimated without the reservation wage are presented in Table A2, in Appendix 2. The results presented in Tables 5.3a and A2 are qualitatively very similar, and indicate that the reservation wage is not endogenous, which implies that simultaneity bias is not present in the results presented in Table 5.3a.

The Wald statistics show that the model coefficients are jointly statistically significant at conventional levels for all eight modes reported in the table.

Table 5.3a: Logit and probit estimates of unemployment duration

	1	2	3	4	5	6	7	8
Reservation wage*1000	-0,02	-0,01	-0,02	-0,01	-0,08	-0,05	-0,08	-0,05
Gender	-0,43	-0,27	*-0,51*	*-0,32*	-0,33	-0,21	-0,34	-0,22
Age	**0,03**	**0,02**	**0,03**	**0,02**	***0,05***	***0,03***	***0,05***	***0,03***
Education: Incomplete Primary	-0,95	-0,55	-0,80	-0,46	-0,42	-0,31	-0,46	-0,33
Education: Complete Primary	-0,54	-0,28	-0,42	-0,21	0,66	0,34	0,63	0,32
Education: Incomplete Secondary	-0,64	-0,36	-0,51	-0,28	0,10	0,004	0,07	-0,20
Education: Complete Secondary	*-1,48*	*-0,87*	*-1,38*	*-0,81*	-0,01	-0,06	-0,07	-0,10
Education: Post-secondary	*-1,43*	*-0,82*	-1,22	-0,71	0,17	0,04	0,11	0,001
Race: Asian/Indian								
Race: African	-0,73	-0,48	-0,84	-0,54	0,92	0,55	0,92	0,55
Race: Coloured	-0,60	-0,42	-0,75	-0,52	0,26	0,14	0,26	0,14
Marital Status	0,16	0,10	0,15	0,08	-0,04	-0,03	-0,05	-0,03
Per capita income*1000	*0,14*	*0,09*	*0,09*	0,06	*0,13*	*0,08*	*0,12*	*0,08*
Urban	0,32	0,18	0,33	0,20	0,05	0,03	0,05	0,03
HH size	**0,14**	***0,09***	***0,19***	***0,12***	-0,03	-0,02	-0,03	-0,02
HH grant	-0,40	-0,24	-	-	0,16	0,09	-	-
HH pension	-	-	**-0,49**	**-0,29**	-	-	0,08	0,03
HH child	-	-	-0,73	-0,46	-	-	0,06	0,03
N	277	277	277	277	347	347	347	347
Pseudo R2	0,12	0,12	0,13	0,13	0,10	0,10	0,10	0,10
Wald	38,64	43,60	44,18	49,50	41,54	45,93	41,46	45,95
P(wald)	**0,02**	**0,01**	**0,01**	***0,00***	**0,01**	***0,00***	**0,01**	***0,00***

Notes: (1) = logit, w3, HH grant; (2) = probit, w3, HH grant; (3) = logit, w3, HH pension and HH child grant; (4) = probit, w3, HH pension and HH child grant; (5) = logit, w4, HH grant; (6) = probit, w4, HH grant; (7) = logit, w4, HH pension and HH child grant; (8) = probit, w4, HH pension and HH chlid grant. Robust standard errors were used to obtain test statistics; ***bold italic***, **bold**, *italic* denote p-values less than 0.01, 0.05 and 0.1, respectively. All estimated equations include provincial dummies.

The reservation wage estimates have negative coefficients in all the models, indicating that job seekers with higher reservation wages were less likely to be long-term unemployed. However, none of the coefficients were statistically significant at conventional levels.

The gender coefficients were negative in all the models, indicating that women are more likely than men to be long-term unemployed. The gender coefficients in columns 3 and 4, which are for the logit and probit that include household receipt of income from a government pension or child support grant, are statistically significant at the 10% level. These coefficients are not significant at conventional levels in the other duration models.

The coefficients for age are positive in all the models, which indicates that older workers were more likely to be long-term unemployed. The age coefficients are also all statistically significant at conventional levels (at the 5% level in wave 3 and at the 1% level in wave 4).

All the education coefficients are negative in the wave 3 models: all those who are unemployed with at least some schooling are less likely than those unemployed with no schooling to be long-term unemployed. The coefficients on complete secondary education are statistically significant at 10%. Furthermore, the coefficients for post-secondary education, in the wave 3 logit and probit that include household receipt of income from a government grant are also statistically significant at the 10% level.

In the wave 4 duration models, the coefficients on incomplete primary and complete secondary are negative, as is the coefficient on incomplete secondary in the probit model which includes household receipt of income from a government pension or a child support grant. This indicates that these unemployed people are less likely than those with no schooling to be long-term unemployed. On the other hand, the coefficients for complete primary and post-secondary education are positive in all of the wave 4 duration models, as are those for incomplete secondary in both logit models, as well as the probit that included household receipt of income from a government grant. This indicates that these unemployed people are more likely than those with no schooling to be long-term unemployed. However, none of the education coefficients in the wave 4 duration models are statistically significant.

The coefficients for marital status are positive in the wave 3 models and negative in the wave 4 models. This indicates that people who were not married or living with a partner are more likely to be long-term unemployed in the wave 3 models, while they are less likely to be long-term unemployed in the wave 4 models. However, none of the coefficients are statistically significant at conventional levels.

The coefficients for income per capita are positive in all the duration models, indicating that people residing in higher income households are more likely to be long-term unemployed. Only the coefficient on per capita income in the wave 3 probit controlling for household receipt of income from a government pension or a child support grant is not statistically significant at conventional levels.

The household size coefficients are positive in the wave 3 duration models, while they are negative in the wave 4 models. This indicates that members of larger households are more likely to be long-term unemployed in wave 3, and less likely to be long-term unemployed in wave 4. However, only the wave 3 duration models' household size coefficients are statistically significant at conventional levels.

The coefficients on household government grant recipient are negative in the wave 3 duration models and positive in the wave 4 models. This indicates that unemployed people who were members of households that received income from a government grant are less likely to be long-term unemployed in the wave 3 models, and more likely to be long-term unemployed in the wave 4 models. However, none of the coefficients on household grant receipt were statistically significant in the duration models of either wave.

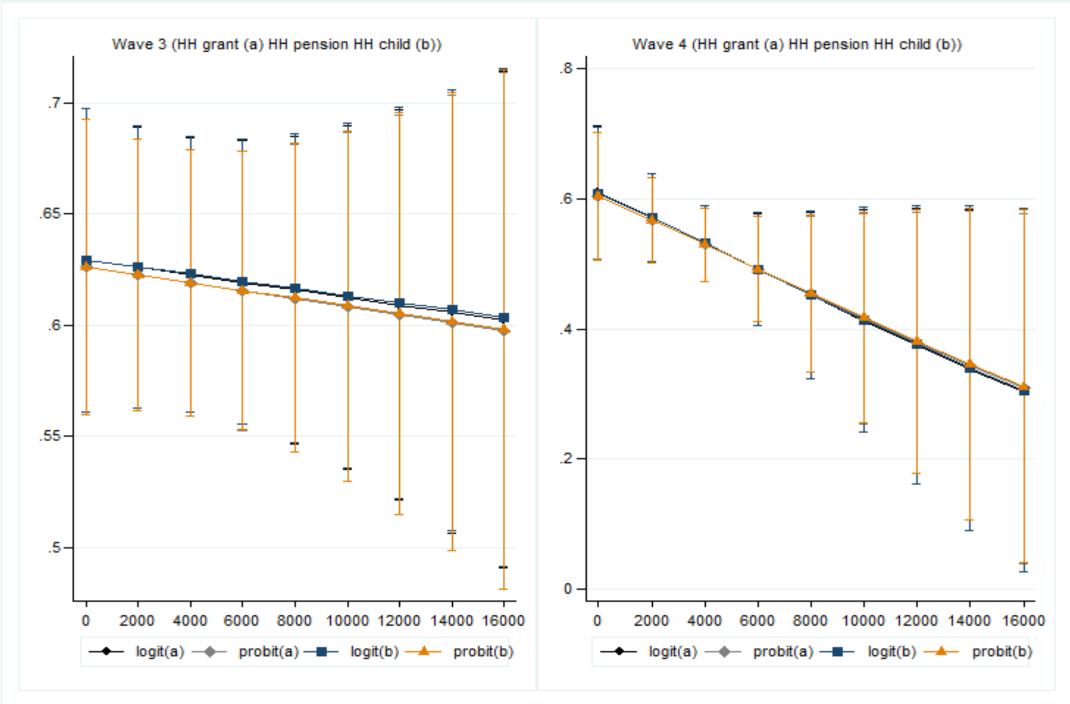
The coefficients on household receipt of income from a government pension or child support grant are negative in the wave 3 duration models, and positive in the wave 4 models. This indicates that unemployed people residing in households where income from either grant is received, are less likely to be long-term unemployed in the wave 3 models, and more likely to be long-term unemployed in the wave 4 models. Only the coefficients on household receipt of a government pension in the wave 3 models are statistically significant at conventional levels.

To facilitate the interpretation on the coefficients reported in Table 5.3a, I estimated the predicted probabilities of unemployment duration over different values of key explanatory variables. I present and discuss the predicted probabilities for the reservation wage, gender, age and education to determine how these variables affect unemployment duration.

The figures that report the predicted probabilties show the results of the wave 3 duration models on the left hand side, and the results of the wave 4 duration models on the right hand side. In each panel, four sets of predicted probabilities are reported: the logit and probit estimates for the models that include the HHgrant dummy variable and the logit and probit estimates for the models that include the HHpension and HH child grant dummy variables instead.

Figure 5.3a below shows the predicted probabilities of unemployment duration by the reservation wage.

Figure 5.3a Predicted probabilities of unemployment duration by reservation wage

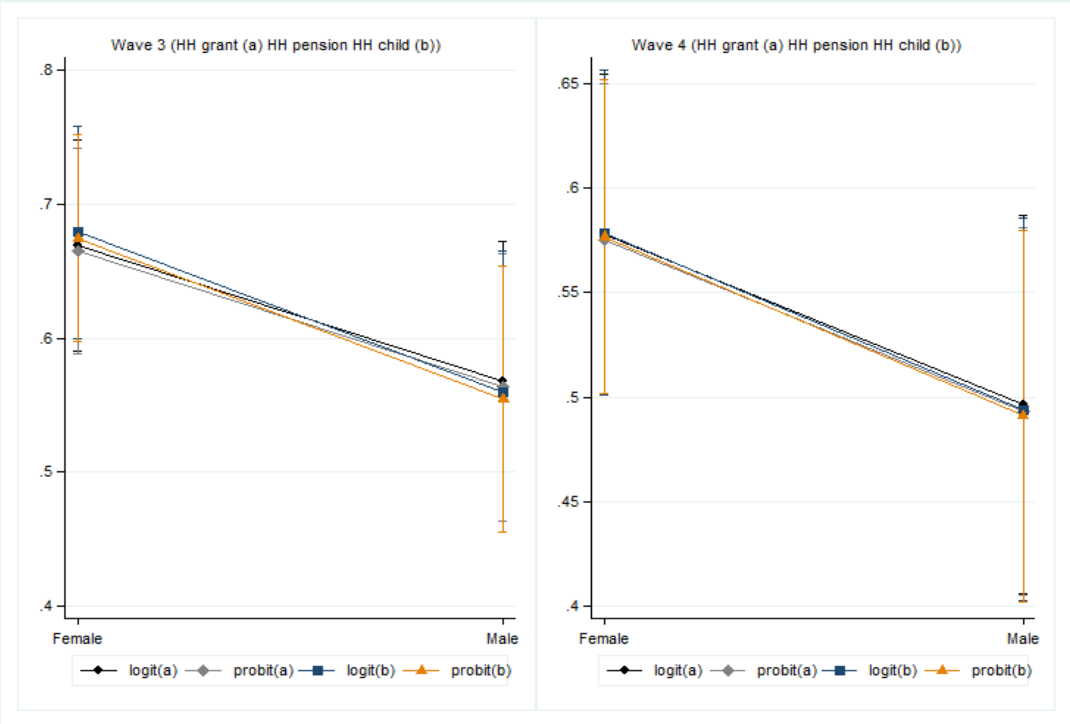


Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

As Figure 5.3a shows, the predicted probability of long-term unemployment decreases as the reservation wage increases. The predicted probabilities of long-term unemployment are higher across different values of the reservation wage in in the wave 3 duration models than in the wave 4 duration models, while the negative slope of the predicted probabilities is much steeper in the duration models for wave 4. The four predicted probabilities in each panel are very similar. These results are in line with the results from the OLS estimation for young US white males in Holzer (1986) and the instrumental variable estimation of Heath and Swann (1999).

Figure 5.3b shows the predicted probabilities of unemployment duration by gender.

Figure 5.3b Predicted probabilities of unemployment duration by gender

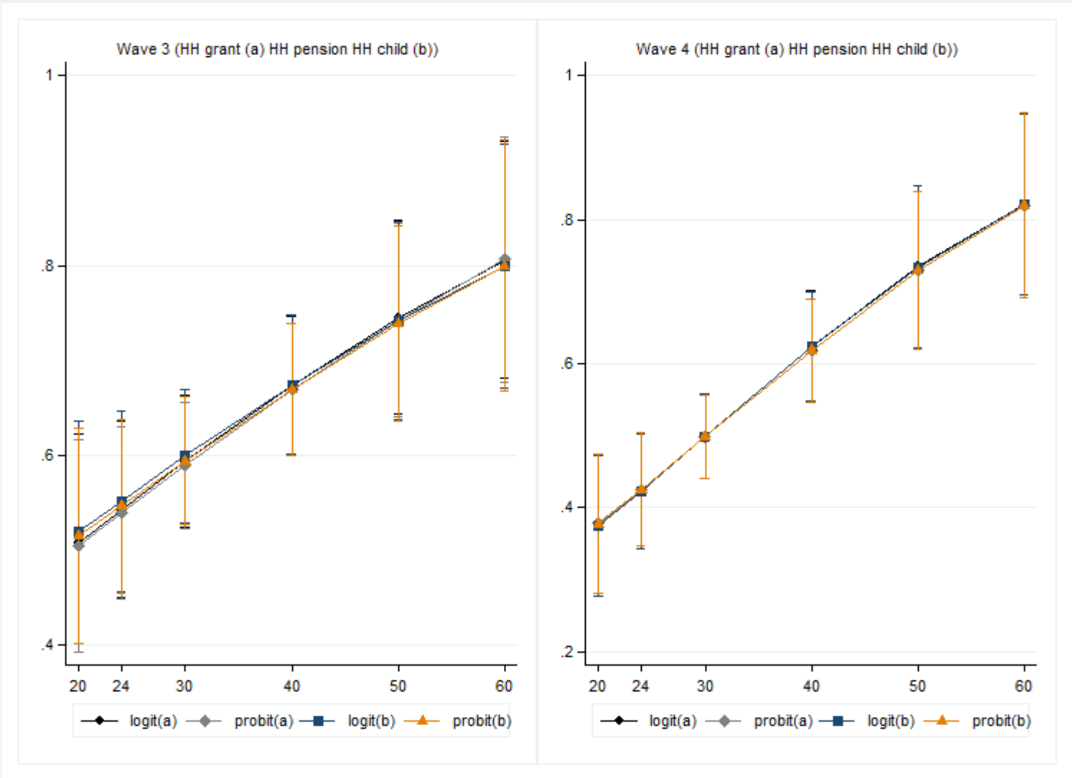


Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

Figure 5.3b shows that the predicted probabilities of long-term unemployment for men are lower than for women. The predicted probabilities of long-term unemployment are lower in wave 4 than in wave 3, while the four predicted probabilities reported in each panel are very similar.

Figure 5.3c shows the predicted probabilities of unemployment duration by age.

Figure 5.3c Predicted probabilities of unemployment duration by age

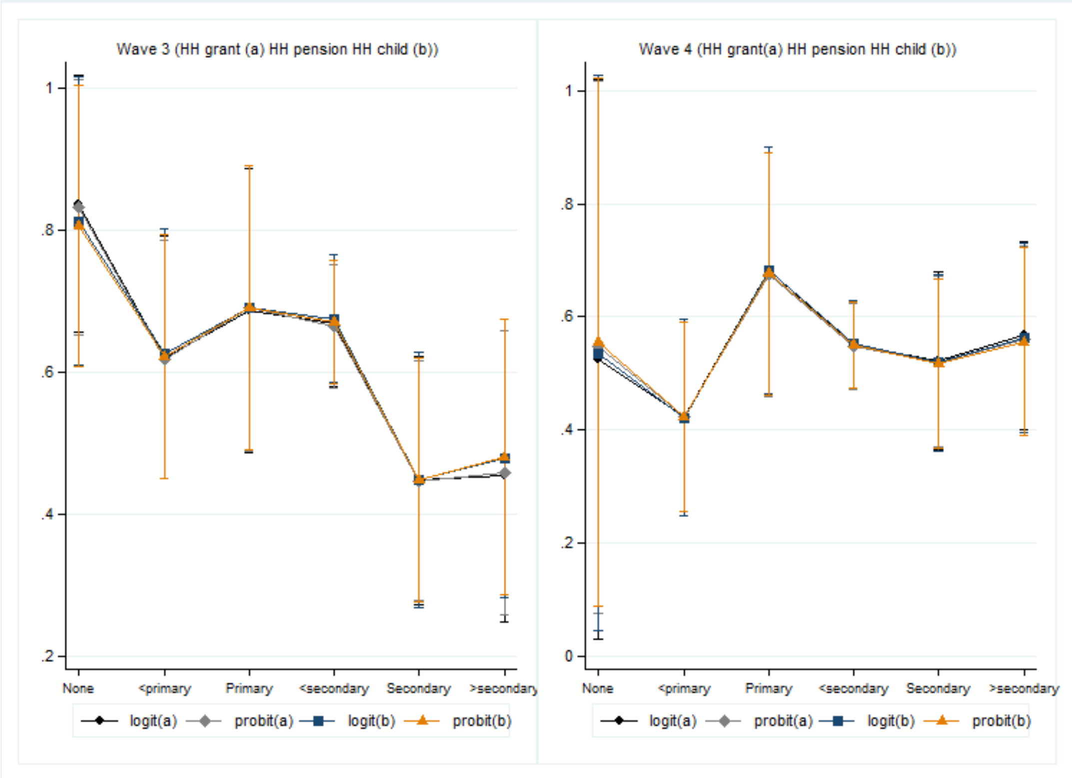


Source: NIDS W3 and W4 data, estimated from coefficients. Author's own calculations.

Figure 5.3c shows that younger workers have lower predicted probabilities to be long-term unemployed. The predicted probabilities for long-term unemployed increase with age in both waves 3 and 4. Younger workers have higher predicted probabilities of long-term unemployment in wave 3 than in wave 4, whereas older workers have similar predicted probabilities in waves 3 and 4. The four predicted probabilities reported in each panel are very similar. These results are in line with those of Uysal and Pohlmeier (2011).

Figure 5.3d shows the predicted probabilities of unemployment duration by level of education.

Figure 5.3d Predicted probabilities of unemployment duration by level of education



Source: NIDS W3 and W4 data, estimated from coefficients. Author’s own calculations.

Figure 5.3d shows that the predicted probabilities of long-term unemployment do not increase or decrease uniformly with the level of education. Qualitatively, the predicted probabilities from the duration models for the two waves behave similarly: the predicted probability decreases from no education to some primary, then increases from some primary to complete primary, then decreases to some secondary and again to complete secondary, before increasing from complete secondary to post-secondary. But the magnitudes of these changes are different between the two waves’ duration models. The largest differences are the following: for the wave 4 duration models, the increase in the predicted probabilities are larger as the level of education increases from some to complete primary, as are the subsequent decreases in the predicted probabilities as the level of education increases to some secondary. Meanwhile, in the wave 3 duration models, the decrease in the predicted probabilities from some secondary to complete secondary is more pronounced. Again, the four predicted probabilities reported in each panel are very similar. A non-linear relationship between level of education and unemployment duration was also found in Kettunen (1997), Riddell and Song (2011) and Uysal and Pohlmeier (2011).

5.5 Conclusion

In this chapter, I presented and discussed the regression results of the binomial unemployment transitions, multinomial unemployment transitions and the unemployment duration models. These regression results can briefly be summarised as follows:

Men, prime-aged workers, those with more education, those who were short-term unemployed, and those with higher reservation wages tended to be more likely to transition to employment than women, younger workers, those with less education, the long-term unemployed, and those with lower reservation wages. Furthermore, transitions to inactivity were more likely for women, those with very low levels of education, the long-term unemployed, and those with low reservation wages.

Men were less likely to be long-term unemployed than women, those with higher reservation wages were less likely to be long-term unemployed than those with lower reservation wages, those who completed secondary education tended to be less likely to be long-term unemployed than those with less education, and older workers were more likely to be long-term unemployed than younger workers.

Chapter 6: Conclusion

6.1 Introduction

This chapter concludes the study by summarizing the main results that I obtained. Furthermore, it also describes the limitations and contributions of the study, makes recommendations for future research, and makes some recommendations for policymakers.

6.2 Summary of the results

The aim of this study was to investigate the effect of reservation wages on transitions from unemployment, as well as on the duration of unemployment. To address these objectives, I used data from the third and fourth waves of NIDS, and estimated transition matrices, as well as binomial and multinomial logit and probit regressions to model unemployment transitions, and binomial logit and probit regressions to model unemployment duration.

Both the descriptive and regression analyses established that a significant, positive relationship exists between reservation wages and transitions to employment. These results are line with those of Poterba and Summers (1995) who also found a positive relationship between reservation wages and transitions to employment, while contradicting those of Addison, Centeno and Portugal (2004) and Burger, Piraino and Zoch (2017), who found a negative relationship between reservation wages and transitions to employment. The results also contradict the theoretical model of job search theory, which predicts that higher reservation wages are associated with a lower probability of transitioning to employment. A possible explanation for this contradiction is that certain individual characteristics , such as higher levels of education and being male, are positively associated with reservation wages and the probability to transition to employment, while also being positively associated with reported wages. Another possibility, which was also mentioned by Krueger and Mueller (2014), is that job seekers are accepting job offers with offered wages that are lower that their reservation wages.

The descriptive and binomial regression results also showed a positive relationship to exist between reservation wages and transitions to inactivity. This relationship was statistically significant at conventional levels in the transition models (in the multinomial transition models, this relationship was found to be positive, but insignificant). These results contradict those of Poterba and Summers (1995), who found a negative relationship between reservation wages and transitions to inactivity.

Results from the descriptive analyses revealed that across age groups, levels of education and genders, those who transitioned to employment had higher reservation wages than those who remained unemployed (with the exception being searching unemployed pension-aged workers). For the searching and non-searching unemployed, statistically significant differences in mean reservation wages between those who remained unemployed and those who transitioned to employment were found for the following groups: prime-aged workers, those with incomplete primary education, complete primary education, and incomplete secondary education, as well as for men and women.

Furthermore, for the searching unemployed, those who transitioned to inactivity had higher reservation wages than those who remained unemployed (the only exception being pension-aged workers). For these people, I found statistically significant differences for prime-aged workers and those with incomplete primary education. For the non-searching unemployed who transitioned to inactivity, young workers, pension-aged workers, workers with no schooling, those with incomplete secondary education and post-secondary education, and men, reservation wages were lower than for those in these categories who remained unemployed. Those with incomplete primary-, complete primary-, and incomplete secondary education, prime-aged and old workers, and women who transitioned to inactivity had higher reservation wages than those in these categories who remained unemployed. None of the differences in mean reservation wages for the non-searching unemployed were statistically significant at conventional levels.

The results from the binomial and multinomial transition models indicated that long-term unemployment was associated with lower transition rates from unemployment to employment, indicative of negative duration dependence. Furthermore, the descriptive analyses, as well as the results of the duration logit and probit models, showed a negative relationship to exist between reservation wages and long-term unemployment: people with higher reservation wages were less likely to be long-term unemployed. These results are also in line with the results from the OLS estimation for young US white males in Holzer (1986) and the instrumental variable estimation of Heath and Swann (1999), who also found a negative relationship between reservation wages and long-term unemployment. But they contradict the WLS results of Holzer (1986) for young white and black US males, as well as the OLS results of Heath and Swann (1986), who found a positive relationship between reservation wages and long-term unemployment. The results also contradict the theoretical model of job search theory, which predicts that higher reservation wages are associated with longer unemployment duration. Again, a possible explanation for the contradiction is that certain individual characteristics, like a higher level of education, or being male, are positively associated with higher reservation wages, while being positively associated with transitions to employment, and therefore negatively associated with unemployment duration. The observation by Krueger and

Mueller (2014) also deserves mention here again as a possible explanation: accepted wage offers by job seekers may be lower than their stated reservation wages.

Descriptive and regression analyses revealed that older workers were more likely to transition to employment relative to remaining unemployed. Furthermore, age was statistically significant in the binomial and multinomial transition models that excluded long-term unemployment. These results are in line with those of Brick and Mlatsheni (2008), Dinkelman (2004) and Mlatsheni and Leibbrandt (2015), whose results also indicated a positive coefficient for age. Furthermore, both the descriptive and regression analyses showed that older workers were also more likely to transition to inactivity relative to remaining unemployed.

In the duration models, older workers who remained unemployed in wave 4 were more likely to be long-term unemployed. These results are in line with those of Uysal and Pohlmeier (2011) whose results also indicated that a positive relationship between age and duration of unemployment, while contradicting the findings of Algan et al. (2003) and Détang-Dessendre and Gaigné (2006), whose results indicated a negative relationship between age and duration of unemployment..

Education was not statistically significant in explaining unemployment to employment transitions in both the binomial and multinomial transitions. Depending on the estimation method (logit or probit) and whether long-term employment was included, both the binomial and multinomial transition models found that those with post-secondary, completed secondary and completed primary education were more likely to transition to employment relative to no schooling.

The binomial- and multinomial transition models found that those with any level of schooling were less likely to transition to inactivity than those with no schooling, while most of the coefficients were statistically significant at conventional levels.

Those with no schooling were most likely to be long-term unemployed, while those with post-secondary cohort were the least likely to be long-term unemployed. In wave 3, all other levels of education were less likely than no schooling to be long-term unemployed, with significant effects for secondary and post-secondary education. In wave 4, those with incomplete secondary and complete secondary education were more likely than those with no schooling to be long-term unemployed, but none of these effects were statistically significant.

These findings about education are more or less in line with the literature (Kettunen, 1997; Ridell and Song, 2011; Uysal and Pohlmeier, 2011; Mlatsheni and Leibbrandt, 2015; Brick and Mlatsheni, 2008 and Dinkelman, 2004) that higher levels of education are positively associated with transitions to employment, and negatively associated with the duration of unemployment.

Both descriptive and regression analyses found men to be significantly more likely than women to transition to employment, while being significantly less likely to transition to inactivity.

Furthermore, women were more likely to be long-term unemployed than men. These findings are in line with Brick and Mlatsheni (2008), Mlatsheni and Leibbrandt (2015) and Dinkelman (2004), who also found that women were more likely to be long-term unemployed..

6.2 Limitations of the study

The main limitation of this study concerns the data about unemployment duration. NIDS does not capture the full employment histories of respondents, and between waves, the unemployed are only asked about the last job that they had prior to the interview. Seeing that there were about 24 months between the collection of data for the third and fourth waves, respondents could have transitioned between different labour market states several times. Furthermore, most of those not in employment report having never worked before, and have unknown dates of labour market entry, due to their incomplete NIDS labour market histories. This necessitated the use of sub-optimal logit and probit models to model duration (instead of hazard models), with a relatively low number of observations, and therefore low statistical power and large coefficient standard errors. However, as described in the results summary, the results from these models still accorded well with what is known about the characteristics of the long-term unemployed in South Africa.

Furthermore, Kingdon and Knight (2004), Krueger and Mueller (2014) and Burger, Piraino and Zoch (2017) note that self-reported reservation wages might be measured with error. However, as Krueger and Mueller (2014) note, these reservation wages still contain useful information, particularly about employment transition and job acceptance. Additionally, while Kingdon and Knight (2004) expressed concern that those answering reservation wage questions in previous surveys may be reporting what they consider to be a fair wage, as opposed to their actual reservation wage. But in NIDS this concern is addressed, because there are separate questions about fair wages and reservation wages, which implies less confusion about the distinction between the two on the part of respondents, removing one potential source of measurement error for the reservation wage.

6.3 Contributions of the study

The contribution of my study is as follows: it used two waves from a national panel data set to analyse the relationship between reservation wages and unemployment transitions, as well as between reservation wages and unemployment duration in South Africa. It also considered how unemployment transitions, unemployment duration, and mean reservation wages vary with age, education and gender. As such, this study is one of the first since Kingdon and Knight (2004) to use national panel data from South Africa to study the effects of reservation wages on unemployment duration. To the best of my knowledge, it is also one of only a few studies to use South African panel data to investigate how reservation wages affect unemployment transitions in South Africa. The research contributes to the understanding of the relationship between reservation wages, unemployment transitions and unemployment duration in the South African context. Furthermore, the impact of gender, age and education adds further insight into these relationships and provides possible clues for policy direction.

6.4 Recommendations for policymakers

It was unexpected that higher reservation wages are associated with a higher probability to transition to employment. The descriptive statistics indicated that people with more education, and men, had higher reservation wages. They were also found more likely to transition to employment. In contrast, people with lower levels of education and women were less likely to transition to employment. While their reservation wages were lower, their reservation wages were still most probably too high, given their individual characteristics, for example, their level of education. It appears as if there is a good reason, based on the data, why people with higher reservation wages are more likely to transition to employment.

By identifying the role of certain individual characteristics and how they relate to reservation wages, policy can be targeted at addressing those characteristics to translate into significant effects. While this study did not evaluate or model the effects of labour market or other policies on unemployment transitions or unemployment duration, the results suggest that, as is well known in the South African unemployment literature, that government should target its interventions at women, young people and those with low levels of educational attainment, as these groups are those who are most likely to be long-term unemployed, while also being the least likely to transition to employment.

The sheer scale of long-term unemployment also suggests that government provision of income support to working-aged unemployed, perhaps in the form of a basic income grant, should be considered, given the detrimental effects associated with long-term unemployment, if fiscal conditions allow for such support. Additionally, I also recommend that more South African household surveys be conducted that collect data on the complete employment histories of (at least young) South African workers (similar to the Cape Area Panel Survey), to allow for the improved modelling and understanding of the duration of unemployment. Administrative data from the South African Revenue Service (SARS), or linked employer-employee data, will also facilitate further modelling and deeper understanding of the mechanisms that explain unemployment transitions and duration, which would allow for more rigorous, evidence-based policy recommendations to be made.

6.5 Recommendations for future research

For future research, I would like to extend my analysis of unemployment transitions and unemployment duration by using all of the waves of the NIDS data (waves 1 to 5) to establish if the results that I obtained for waves 3 and 4 hold in other waves, as well as if they hold over the entire duration of NIDS. Furthermore, if a national data set containing the complete employment histories of workers becomes available, I would like to use this data to model unemployment duration using hazard models, which are the preferred method for duration models.

6.6 Conclusion

In this chapter, I summarised the main results of the research and discussed the limitations and contributions of this study. Furthermore, I identified recommendations for policymakers and future reseach based on the results of this study.

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Appendix 1: Attrition analysis

Of the 3851 unemployed people in wave 3, 896 (23%) did not form part of wave 4, which is about 10 percentage points higher than the total attrition rate for wave 4 (NIDS, 2018). The table below shows the numbers of people who did and did not attrite by education, age, gender, race and marital status. The table also provides the chi-squared statistic and p-value for the multinomial goodness-of-fit test.

Table A1.3: Characteristics of those who attrited and those who remained

Variable	Attrited (n=)	Remained (n=)
Education		
No Schooling	46 (5.19)	149 (5.05)
Incomplete primary	105 (11.85)	313 (10.60)
Complete primary	54 (6.09)	188 (6.37)
Incomplete secondary	414 (46.73)	1448 (49.05)
Complete secondary	186 (20.99)	626 (21.21)
Higher education	81 (9.14)	228 (7.72)
Chi-squared statistic for multinomial goodness-of-fit (p-value)	4.7461 (0.4476)	
Age		
15 to 24 years	290 (32.51)	1035 (35.05)
25 to 50 years	534 (59.87)	1675 (56.72)
51 to 60 years	38 (4.26)	193 (6.54)
Older than 60 years	30 (3.36)	50 (1.69)
Chi-squared statistic for multinomial goodness-of-fit (p-value)	24.9538 (0.0000)	
Gender		
Male	425 (47.43)	1196 (40.47)
Female	471 (52.57)	1759 (59.53)
Chi-squared statistic for multinomial goodness-of-fit (p-value)	18.0116 (0.0000)	
Other important variables and their distributions		
Race		
African	763 (85.16)	2581 (87.34)
Coloured	104 (11.61)	329 (11.13)
Asian/Indian	10 (1.12)	19 (0.64)
White	19 (2.12)	26 (0.88)
Chi-squared statistic for multinomial goodness-of-fit (p-value)	19.4650 (0.0002)	
Marital status		
Married/Living with partner	161 (23.78)	617 (25.77)
Other	516 (76.22)	1777 (74.23)
Chi-squared statistic for multinomial goodness-of-fit (p-value)	1.4034 (0.2362)	

Notes: Author's calculations using NIDS (W3 and W4) data. Values in parentheses indicate percentages.

The low p-values of the chi-squared statistic for the multinomial goodness-of-fit test based on age, gender and race indicate that there are statistically significant differences in the attributes of the two groups (attrited and remained), which may mean that attrition bias could be present.

Table A1.2 below provides the results of the chi-squared independence tests to determine whether attrition is independent of education, age, gender, race and marital status.

Table A1.4: Chi-squared independence test results between attrition and X

Variable	**Attrition**
Education (n=3838)	3.56 (0.614)
Age (n=3845)	17.55 (0.001)
Gender (n= 3851)	13.66 (0.000)
Race (n=3851)	11.62 (0.009)
Marital status (n=3071)	1.11 (0.293)

Notes: X denotes Education, Age, Gender, Race and Marital status. Chi-squared is the chi-squared test statistic for the test that U2E transition and X are statistically independent (with the p-value of the statistic in parentheses). Author's calculations using NIDS (W3 and W4) data.

The chi-squared statistics and p-values indicate that attrition is not statistically independent from age, gender and race. This may also indicate that attrition bias could be present.

I estimated logit and probit regressions to explain attrition, in which attrition status is regressed on age, race, education, gender, marital status, employment status, household size and per capita household income. The results are reported in Table A1.3 below.

Table A1.5: Explaining the determinants of attrition with logit and probit regressions

Variable	Logit	Probit
Age	-0.0038	-0.0023
Education: Incomplete primary	0.1637	0.0994
Education: Complete primary	0.1307	0.0793
Education: Incomplete secondary	0.0183	0.0132
Education: Complete secondary	0.0644	0.0367
Education: Higher education	0.2928	0.1728
Race: Coloured	0.1879	0.1102
Race: Asian/Indian	0.6954	0.4120
Race: White	*0.7988*	*0.4772*
Male	*-0.1707*	*-0.0995*
Marital status	0.0486	0.0322
Per capita income	4.00E-05	2.00E-05
Household size	***0.0382***	***0.0226***
Employment status	0.1194	0.0687
N	3067	3067
LR	32.82 (0.003)	33.13 (0.0028)
Pseudo R-squared	0.0102	0.0102

Notes: Author's calculations using NIDS (W3 and W4) data. *Italic*, **bold** and ***bold italic*** denote p-values less than 0.1, 0.05 and 0.01, 0.05 and 0.1, respectively.

In both of these attrition regressions, the coefficient on household size is the only coefficient that is significantly different from zero at the 1% level, while the coefficients on male and white are statistically significant at the 10% level. No other coefficient is statistically significant at conventional levels. The Pseudo R^2 value for both the probit and logit regressions is about 0.01. Given these results, it would be inappropriate to correct for attrition using inverse probability weights (IPW) (Booysen and Geldenhuys, 2016). And, as in Booysen and Geldenhuys (2016), all of my unemployment transition and unemployment duration results are reported without IPW to correct for attrition.

Appendix 2: Unemployment duration regressions excluding the reservation wage

Table A2: Logit and probit estimates of unemployment duration excluding reservation wage

	1	2	3	4	5	6	7	8
Gender	-0,46	*-0,28*	*-0,54*	**-0,33**	*-0,42*	*-0,26*	*-0,44*	*-0,27*
Age	**0,03**	**0,02**	**0,03**	**0,02**	***0,05***	***0,03***	***0,05***	***0,03***
Education: Incomplete Primary	-0,97	-0,56	-0,82	-0,47	-0,53	-0,38	-0,57	-0,40
Education: Complete Primary	-0,56	-0,30	-0,45	-0,23	0,43	0,21	0,40	0,19
Education: Incomplete Secondary	-0,68	-0,39	-0,55	-0,31	-0,08	-0,10	-0,11	-0,12
Education: Complete Secondary	**-1,57**	**-0,92**	*-1,49*	**-0,88**	-0,22	-0,19	-0,27	-0,22
Education: Higher Education	*-1,47*	*-0,85*	-1,28	-0,74	-0,23	-0,21	-0,28	-0,24
Race: Asian/Indian								
Race: African	-0,70	-0,46	-0,81	-0,52	0,80	0,49	0,83	0,50
Race: Coloured	-0,56	-0,39	-0,69	-0,48	0,15	0,08	0,20	0,10
Marital Status	0,16	0,10	0,16	0,09	-0,03	-0,03	-0,05	-0,04
Per capita income*1000	0,15	0,09	0,10	0,06	0,08	0,05	0,07	0,05
Urban	0,30	0,17	0,31	0,18	0,07	0,05	0,07	0,05
HH size	**0,14**	***0,08***	***0,18***	***0,11***	-0,03	-0,02	-0,03	-0,02
HH grant	-0,37	-0,23	-	-	0,14	0,08	-	-
HH pension	-	-	-0,49	-0,28	-	-	0,11	0,06
HH child	-	-	**-0,69**	**-0,43**	-	-	0,02	0,01
N	277	277	277	277	347	347	347	347
Pseudo R2	0,12	0,12	0,13	0,13	0,10	0,10	0,10	0,10
Wald	37,73	42,56	43,04	48,31	41,18	45,44	40,92	45,25
P(wald)	0,02	0,01	0,01	0,00	0,01	0,00	0,01	0,00

(1) = logit, w3, HH grant; (2) = probit, w3, HH grant; (3) = logit, w3, HH pension and HH child grant; (4) = probit, w3, HH pension and HH child grant; (5) = logit, w4, HH grant; (6) = probit, w4, HH grant; (7) = logit, w4, HH pension and HH child grant; (8) = probit, w4, HH pension and HH chlid grant. Robust standard errors were used to obtain test statistics; ***bold italic***, **bold**, *italic* denote p-values less than 0.01, 0.05 and 0.1, respectively. All estimated equations include provincial dummies.