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The Impact of Climate Change on Gender Inequality in the Labour Market: A Case Study of South Africa

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Abstract: South Africa has been exposed to climate change and has been experiencing associated extreme climatic events such as droughts, floods, and heat waves. These have impacted water and fuel sources, habitats, human health, and economic productivity. Poorer populations and particularly females are more affected. The main objective of this study is therefore to assess gender inequalities in employment resultant from the effects of climate change and extreme climatic events. The study employs binary, ordered, and multinomial logistic models to analyse the effects on employment, intensity of employment and the effects in economic sectors, respectively. The study computes temperature deviations from its long-run mean as climate change variable and uses the Keetch–Byram Drought Index and number of heatwave days per year as proxies for extreme climatic events. Data for the work are from the South African Weather Services database and the National Income Dynamic Survey. The findings suggest that climate change reduces the probability of being employed more for males than females, but extreme events have more negative effects on female employment than males. We suggest that while climate change mitigations and adaptation measures geared towards the labour market should take priority in general, when extreme climate events occur, labour market support measures should weigh more towards females.

Keywords: climate change; climate shock; vulnerability; gender inequality; labour market; unemployment

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1. Introduction

> "... *One important feature of climate change is that it is not currently, and will not in the future, impact the planet or populations evenly ... climate change has a tendency to reflect and exacerbate the world's worst inequalities, including gender inequalities*" [1] (p. 402)

Empirical studies have highlighted the adverse impacts of climate shocks on various economies. Greater and disproportionate impacts are predicted for low-income countries and more vulnerable and marginalized individuals within these countries [2–4]. There may be short to medium term gains from climate shocks [3], but the full negative and persistent impacts often surface in the longer term [5]. Consequently, in the long run, the adverse effects are expected to outweigh the benefits [3]. Overall, climate change destabilizes markets and human welfare by exacerbating socioeconomic inequalities and exposing vulnerable communities to greater vulnerability.

Common examples of climate shocks include drought, flooding, extreme heat, higher incidence of food insecurity and disease [6]. One of the effects of climate shocks is its impact on wage distribution through restricted access to basic human needs such as nutrition, health care and education [7]. Both developed and developing countries show a tendency of declining productivity as a result of an increase in temperatures [8,9]. Climate change is additionally associated with labour migration both at local [10] and international levels [11]. Over time, this is associated with higher prices, lower employment levels and a shrinking disposable income [12]. A persistent occurrence of these factors culminates in a rise in poverty [13], a decline in consumption [14], health [15] and welfare [12], especially of low-income households [16].

There are various channels through which climate change can affect the labour market. Ref. [17] summarise them into three broad categories. The one is the direct effects of climate change on the natural and built environments. Climate change and associated natural phenomena eventually lead to resource and species depletions, and also deplete aspects of the natural and built environment, such as infrastructure [18], leading to significant impacts on the labour market. An offshoot of the direct effect on natural and built environment is health effects [19]. Ref. [20] points to human health as one of the main avenues through which climate change translates to low levels of labour supply. The second broad transmission channels are the regulatory policies affecting both demand and supply sides of labour. Most climate-related regulatory policies tend to shift production to renewables and climate-smart systems. These mostly apply in developed countries as South Africa's climate policies have not been around long enough to have impact so far. Lastly, the third channels constitute the set of social conscience that drive private agents' decisions, thereby influencing production and labour demand patterns. The latter suggests that the effects of climate change may vary by economic sectors given the expected structural change in production patterns. Certain higher temperatures have been shown to reduce both hours allocated to [21–23] and performance in the labour market [19,24] especially in highly exposed sectors such as agriculture.

In South Africa, the labour market is the principal source of inequality, especially along gender and demographic lines [25]. Females in South Africa represent a larger proportion of the population than their male counterparts [26] and are associated with higher unemployment rates [27]. Women's participation in the labour force is also influenced by enhancements in labour market opportunities. The rise in opportunities is conditioned by increased access to education, marital status, fertility, and geographical location [28]. Surprisingly, to date, no study has delved into the engendered consequences of climate change in the labour market.

Climate shocks are expected to rise in regularity and intensity, with events such as storms and flooding becoming increasingly frequent [29]. It is predicted that this will not only impact mortality but result in injuries, food and water insecurity, as well as a rise in the spread of disease and mental health illnesses [30]. The increment in malaria infections, for instance, is associated with spiking temperatures and changes in precipitation, particularly in Limpopo [31,32]. Climate shocks are further linked to enhanced pre-existing susceptibilities of females, fishing communities, rural subsistence farmers and residents of informal settlements [33]. Females in particular, are excessively vulnerable to climate shocks due to their inherent social responsibilities (energy collection and use) and dependency on traditional sources of fuel (wood, charcoal, agricultural waste), principally in rural areas [34]. In times of hardship, females and children are known to forgo their nutritional [35] and educational needs in search of water and wood to sustain the household [36]. In Goedgevonden village, South Africa, the impact of drought resulted in high pupil absenteeism [37]. In the absence of closely located sources of these fuels, a large proportion of females' time and energy is spent covering long distances in search of them. This exposes them to danger of physical and sexual harm [38]). Consequently, they are time-poor and face a high economic cost of their time usage which could have otherwise been spent on income generating activities [39]. Deforestation resulting from climatic shocks is expected to make this situation direr [36].

As a result, regardless of timeframes, climate change poses a major threat to sustainable development [40]. Notably, many of the most vulnerable populations worldwide are found in Africa and have a high dependence on agriculture [41]. Thus, inequalities that define ownership of assets (e.g., land, income), demographics (e.g., race, gender, religion) and public decision-making (political power) and the access to public goods and service (education, health, financing) are all inter-linked [42]. There is therefore a need for policy measures to reduce exposure to and mitigate the impacts of climate change especially on vulnerable groups, of which women top the list. In South Africa, women are the face of societal inequalities, including unemployment and poverty. This makes South Africa, a useful case to study.

A number of studies have attempted to assess the consequences of climate change in South Africa. A substantial proportion of these focused on the effects of drought. Examples include [33,36,37,43–45]. The studies provide insight into what has been achieved in terms of awareness and adaptation to climate change. However, the studies are based on diverse elements, data sources and research techniques. The findings are thus not comparable across provinces and the country.

Adopting a mixed methods technique [37], analysed the socioeconomic impact of drought. The study was limited to a village in North West province. Nonetheless, the study showed that drought was associated with the loss of livelihoods, learner absenteeism and ill-health. The study also found that the community was mostly composed of female-headed households. The author concluded that there is a need for an adaptation strategy. This includes the need for promotion of economic activities geared towards women. In [46], the author sought to assess the engendered consequences of climate change. The author found that both males and females were adversely impacted by climate change. The females, however, shouldered more workload enduring greater emotional and physical strain. The study indicates that there is a transformation in gender roles. More women seek to diversify their livelihoods, including seeking income generating occupation such as trading. However, this study is based on qualitative research. Another drawback of the study is that it is restricted to rural areas of uMhlathuze and uMzinyathi in KwaZulu Natal province.

Moreover, Ref. [45] employ the SPEI to examine the impact of drought. The authors found a negative relationship between drought and maize production. The severity of the adverse effects depended on planting seasons. This study was however, restricted to the Luvuvhu River catchment area. Added to that, the study only focused on the consequences of drought for maize production.

More comprehensive studies have also been undertaken. However, the studies resorted to a review of literature. Authors in [15] analyse the role of the health sector in climate change adaptation in South Africa. They found that several climate change policy frameworks have been created. Nonetheless, the study shows that marginal consideration is given to the health concerns and requirements of the vulnerable. Neither the country in general, nor the health sector in particular, show response readiness to deal with climate shocks. The authors of [47] assess the impact of drought in South Africa by economic sectors (agriculture, livestock, tourism, mining, agro-processing, small and large businesses, and water quality). The study found that drought constrains productivity in the various sectors. The extent of constraint is however, determined by each sector’s dependency on water. In [48], the authors investigated the effect of climate change and adaptation. The authors concluded that the country has made progress in the analysis of the consequences of and execution of adaptation response to climate change. Nevertheless, the progress has been centered around water, agriculture, and biodiversity. The study recommends further research into the effect of and particularly the socioeconomic consequences of climate change. The author of [36] examined the relationship between gender, climate change and energy in South Africa. The study found that the country has made huge strides in creating a legislative framework and policy. The challenge remains how to sustainably integrate gender and energy interests with climate mitigation strategies. The author concluded that females are still overly predisposed to climate change in comparison to their male counterparts. This is principally because they constitute the larger proportion of the population. They are also the face of poverty. This is exacerbated due to the intrinsic gendered division of labour. They are engaged in sectors that are dependent on climate change. For example, they are responsible for the collection and use of energy resources such as firewood. In general, these studies indicate to a need for more evidence-based research at a large scale.

Considering the different socioeconomic dynamics of the various provinces of South Africa, a comprehensive study of the consequences of climate change is warranted. Knowledge gaps still exist in relation to the socioeconomic implications of climate change nationwide. Still more, it is not enough to merely acknowledge that climate change impacts men and women differently. There is a need to pinpoint what these differences are, how they constrain response and adaptation to climate shocks. There is also a need to quantify them where possible. This paper builds on [46] to include a quantitative analysis at country level. Given the labour market's crucial role in engendering socioeconomic inequalities in South Africa, we focused our assessment on the effects of climate change on employment. We further analyse the possible impacts on structural transformations in the labour market. In addition, the study brings to light potential gendered consequences thereof, given females' lower employment levels and greater susceptibility to climate change.

This work therefore assesses the effect of climate change and climatic shocks on the labour market outcomes along gender lines in South Africa. Specifically, the work seeks to:

1. Assess the role of climate change and climatic shocks on unemployment and under-employment.
2. Assess the effect of climate change and climatic shocks on employment intensity.
3. Analyse the effect of climate change on the structure of employment.

2. Materials and Methods

This section will discuss the theoretical and empirical frameworks that guided this work. The various data and respective sources will also be presented here. We conclude this section with a discussion of the estimation strategies employed.

2.1. Theoretical Framework

The theoretical framework for labour demand and supply follows [10]. In the framework, utility (U) is obtained from the consumption of both non-agricultural goods and services (X_{na}) and agricultural goods (X_a). The output is a function of labour (L) and quasi-fixed capital and land ($\overline{K}$), i.e., $Q = f(L, \overline{K}, \theta)$. We presuppose that $f_L > 0$, $f_\theta > 0$, $f_{LL} < 0$, and $f_{L\theta} > 0$. θ is a random variable which denotes the good weather. The higher the value of θ the better the weather. Consequently, the more the production. Additionally, the weather and labour are considered to be complements. The household is a price-taker, and its utility is constrained by income. The income constraint incorporates profits from agricultural activities and the household's time, such that:

$$max_{L,X_a,X_{na},X_1} U\ (X_a,\ X_{na},\ X_1) s.t.\ p_a X_a + p_{na} X_a + wX_1 = Y = p_a f\left(L, \theta; \overline{K}\right) - wL + wT \quad (1)$$

where p_a is the price of agricultural goods, p_{na} is the price of non-agricultural goods, $p_1 = w$ and denotes the price of local wage, and T is the household's time endowment. Solving for the production side we obtain Equation (2):

$$p_a f_L\left(L,\ \theta,\ \overline{K}\right) = w \quad (2)$$

Such that the demand for labour can be presented as $L^*\left(p_a,\ w, \overline{K},\ \theta\right)$. That is, it is conditional on the weather, capital and prices locally. Climate shocks impact agricultural production negatively. Therefore, we expect an inverse relationship between climate shocks and the demand for agricultural labour. Utility is then maximised conditional on the best full income outcome $Y^* = p_a f\left(L^*,\ \theta; \overline{K}\right) - wL^* + wT$. This results in the following consumption demands:

$$X_i^*(p_a,\ p_{na},\ w,\ Y^*) \quad (3)$$

The family labour supply is denoted by F^*. It is derived from the trade-off between time endowment and the demand for leisure:

$$F^*(p_a,\ p_{na},\ w,\ Y^*) = T - X_1^* \quad (4)$$

A household that is lacking in labour will hire it for production, i.e., $H^* > 0$. Leisure is, however, presumed a normal good. Thus, a fall in income leads to an increment in labour supply at the household level. Conversely, this translates to a fall in the demand for labour:

$$H^*(p_a,\ p_{na},\ w,\ Y^*) = L^* - F^* = L^* - (T - X_1^*) \tag{5}$$

Consequently, there is a decline in hired labour (H^*).

Given the income constraint, a decline in agricultural income impacts non-agricultural goods demand negatively. Moreover, services that are characteristically non-tradable make up a substantial component of non-agricultural consumption demand in poor rural economies. Hence, based on the local market-clearing restraint, the equilibrium price and quantity are attained where overall household demands equate to the services supplied (S):

$$\sum X_{na}^*(p_a,\ p_{na},\ w,\ Y^*) = S(p_{na},\ w,\ K_{na}) \tag{6}$$

As with the demand for agricultural goods, a decrease in the demand for services yields a decrease in prices. This results in a fall in the demand for non-agricultural labour. This includes hired labour. As a result, we expect climate shocks to negatively impact employment.

The theoretical gender dimension basis follows [28]. The underlying theory dictates that a female's labour market participation decision is determined by the outcome of the appraisal of her expected market wage offer (W_i) and her reservation wage (W_r) (value of time in other activities other than market-related). Her decision to participate is conditional on the expected market wage offer being larger than the reservation wage, i.e.,

$$(W_i)\ >\ W_r \tag{7}$$

so that components influencing changes in either W_i or W_r will result in a rise or decline in the labour market participation.

Female labour force participation in South Africa is mainly determined by education, experience, gender, race, age, geographic location, marital status, fertility, and non-labour income [49]. We focus on gender, education, age, marital status, non-labour income and geographic locale. We further argue that it is also influenced by weather events. Our expected theoretical outcomes are as follows: (i) Gender—ambiguous relationship. Generally, the country has recorded a higher participation for men over women [26]. We expect the results to reflect the status quo. (ii) Education—a positive association. Investments in education often translate to greater ability. This is associated with higher earnings. As a result, the trade-off of labour for leisure becomes costly. This increases chances of participation in the labour force [50] (iii) Age—we expect an inverted U relationship. (iv) Marital status—ambiguous outcome is expected. Theory suggests that intra-household decisions and income security impacts participation decision. Therefore, there is a higher likelihood of participation for single compared to married females. (v) Non-labour income—we expect an inverse relationship. This alternative income provides a sense of financial security which lessens the pressure to participate in the labour market [49]. (vi) Geographic location—theory postulates an ambiguous association. Higher levels of unemployment expected for rural as opposed to urban areas. (vii) Climate shocks—negative association is expected. Generally, climate shocks allude to lower production and productivity [51]. This influences a lower demand for labour.

2.2. Functional Forms

2.2.1. Assessing the Role of Climate Change and Climatic Shocks on Unemployment

Guided by the theoretical framework discussed above, we estimate the models below. The methodology relies on models of labour market participation and labour supply. The following specification fits the purpose:

$$U^*_{ijt} = \beta_0 + \beta_1 G_{ijt} + \beta_2 ED_{ijt} + \beta_3 AGE_{ijt} + \beta_4 AGE^2_{ijt} + \beta_5 MSTAT_{ijt} + \beta_6 NLINC_{ijt} + \beta_7 URB_{ijt} + \beta_8 C_{jt} = \mu_{it} \quad (8)$$

with

$$P(U_{ijt} = 1 | X_{ijt}, C_{jt}) \Phi(\beta_0 + \beta_i X_{ijt} + \beta_i C_{jt}) \quad (9)$$

where U is unemployment; C is a vector of variables related to climatic conditions and shocks; X denotes a vector of control variables including individual heterogeneities (gender, age, age squared, education, geographic location, etc.), community characteristics, etc.; and μ_{it} is the error term. The subscript i indexes individual observation, in j municipality at time t. Since we are interested in labour market participation, the outcome (U) can assume the different labour market participation that would be employed, and various definitions of unemployed. Equation (8) was estimated for males and females separately. The estimation of the model relied on a logit/probit-type approach. A multinomial logit was also employed. The explanatory variables are presented below:

G = Binary variable for gender = 1, if female, 0 otherwise (male).
ED = Categorical variable for educational attainment = 1, if one falls within one of the following categories: Incomplete Primary, Complete Primary, Incomplete Secondary, Secondary, National Technical and Certificate, Post-Secondary and Diploma, Degree, and 0 otherwise (no education).
AGE = Continuous variable for age. Age range from 15 to 64 years of age.
MSTAT = Categorical variable for marital status = 1, if one falls within one of these categories: Cohabiting, Widowed, Divorced/Separated and Never Married, and 0 otherwise (married).
NLINC = Binary variable for Non-Labour Income = 1, if the household or member of the household gets any income from other sources other than labour, e.g., pension, disability grants, remittances or childcare grant, 0 otherwise.
LOC = Binary variable for location = 1, if in urban area, and 0 otherwise (rural).
C = Continuous variable indicating climatic conditions and shocks.

It is plausible that one's unemployment outcome can also be influenced by the relationship between the independent variables which define the expected output. For the sake of this study, we were interested in examining the impact of climate events on employment outcomes given the impact of the climate events on gender. As a result, we approximate separate interaction models for females (Equation (10)) and males (Equation (11)). The female and male interaction models are estimated as follows, respectively:

$$\begin{aligned} U^{*\,f}_{ijt} = {} & \beta_0 + \beta_1 F_{ijt} + \beta_2 ED_{ijt} + \beta_3 AGE_{ijt} + \beta_4 AGE^2_{ijt} + \beta_5 MSTAT_{ijt} + \beta_6 NLINC_{ijt} \\ & + \beta_7 URB_{ijt} + \beta_8 C_{jt} + \beta_9 F_{ijt} * C_{jt} + \mu_{it} \end{aligned} \quad (10)$$

$$\begin{aligned} U^{*\,m}_{ijt} = {} & \beta_0 + \beta_1 M_{ijt} + \beta_2 ED_{ijt} + \beta_3 AGE_{ijt} + \beta_4 AGE^2 + \beta_5 MSTAT_{ijt} + \beta_6 NLINC_{ijt} \\ & + \beta_7 URB_{ijt} + \beta_8 C_{jt} + \beta_9 M_{ijt} * C_{jt} + \mu_{it} \end{aligned} \quad (11)$$

2.2.2. Assessing the Role of Climate Change and Climatic Shocks on Underemployment

Shocks may not completely exclude categories of individuals from the labour market but may rather result in lower levels of labour supply or underemployment. Underemployment is generally defined conditional on time and scarce employment opportunities. This study focused on the time-based underemployment which is loosely defined to refer to individuals who are employed but for lesser hours than they are willing and able to [52]. They are expected to be associated with lower wages and consequently lower welfare levels. The Basic Conditions of Employment Act of South Africa stipulates a 45 h working week. For this purpose, we specify a model similar to Equation (8), but with a dependent variable capturing weekly hours offered to the labour market (L).

$$L^*_{ijt} = \beta_0 + \beta_1 G_{ijt} + \beta_2 ED_{ijt} + \beta_3 AGE_{ijt} + \beta_4 AGE^2_{ijt} + \beta_5 MSTAT_{ijt} + \beta_6 NLINC_{ijt} + \beta_7 URB_{ijt} + \beta_8 C_{jt} + \mu_{it} \quad (12)$$

The dependent variable varies from 1 to maximum weekly hours worked (maximum possible is 168 h per week). The distribution of the hours worked would likely follow a Poisson, or a binomial distribution. The choice of the binomial over the Poisson model was informed by the behavior of the variable. For robustness, selection-type modelling was applied, specifically the Heckman model. Equations (8), (9) and (12) were estimated for males and females separately.

2.3. Data and Variables

The non-climate variables are from the National Income Dynamics Survey (NIDS) database. The dataset covers a two-yearly period ranging from 2008 to 2017. The NIDS is managed by the Southern Africa Labour and Development Research Unit (SALDRU) of the University of Cape Town. It is a nationwide survey which gathers livelihood information at individual and household levels in South Africa. This includes information on income, expenditure, assets and general well-being. To date five waves of the study have been undertaken, encompassing the period 2008 to 2017. Labour market information and other covariates were obtained from the NIDS. The sample consists of individuals aged between 15 and 64, that is, officially considered to be of working age [25].

2.3.1. Climate Related Variables

The climatological data were obtained from the South African Weather Services (SAWS). The SAWS database consists of panel data for rainfall, daily surface observations, weather elements data such as wind direction, humidity, and sunshine, marine and forecasting data. Longevity of datasets vary with some such as rainfall data dating as far back as 1836. Complementary climatic data were sourced from the Council for Scientific and Industrial Research (CSIR). The CSIR performs research and technological innovation in various areas geared towards socioeconomic development in South Africa. This includes a disaggregated panel dataset that can be matched to the NIDS datasets. We capture climate change and climate events using different indicators: namely, deviations from the long-run means, positive and negative deviations, and extreme weather events.

Long-term deviation measures: The variables capturing climate change are calculated at different levels. The first level relates to temperature and rainfall. In line with prior research [9], to distinguish simple year-on-year variations from actual climate change we calculated the year-on-year deviation from the long-run means of the temperature and rainfall. The long-term mean is the mean for each district municipality from 1970 to 2017. We then calculated the annualised standard deviation of temperature relative to the long term mean to get year-on-year deviation which we consider as the temperature shocks. We did a similar computation for rainfall.

Positive and negative deviations: Besides the temperature and rainfall shocks it is possible that there may be asymmetric shocks depending on whether we are on the positive or negative side of temperature increase. It is not only extreme hot temperatures that may have effect on labour supply. Extreme cold may also have an effect on labour supply. For this purpose, we computed the degree of deviation from the long-run mean from the positive (Tdev.+) and the negative (Tdev.−) sides.

Extreme weather events: It is plausible that although actual temperature and rainfall shocks might affect labour supply, occurrences of weather events like droughts and heatwaves might equally be significant not only in determining labour supply but also in determining gender differences. This consideration is more important because during periods of calamity gender roles become more prominent. For this reason, we computed an index of heat wave days (HWD) which is the sum of days experiencing heat waves each year. Another weather event of interest is drought. We used the Keetch–Byram Drought Index (KBDI) to compute these weather events. The KBDI is a scale which computes moisture or lack thereof in soil and respective organic/dirt levels. It is usually used to forecast the occurrence of wildfires. The index is estimated based on daily temperatures and rainfall, with an interval between 0 and 800. Moreover, 0 denotes the highest levels of moisture and 800 the lowest (severe drought) [53]. The KBDI is estimated as $KBDI = 8 * (100 - FC)$. For this study the KBDI was computed based on the fire danger days, heat wave days and very hot days. The variables used for computation of this index were obtained from the SAWS database.

2.3.2. Other Control Variables

The theory underlying the labour market model above suggests that key control variables to absolutely include in the model relate to education, geographic location, non-labour income, marital status, and age. The education variable was divided into 8 classes—the uneducated, followed by various categories of academic attainment from primary through to tertiary. Geographic location was subdivided into 2, namely, rural, and urban. Non-labour income was calculated as the sum of all incomes from non-labour market sources. Examples include grants, pension, and remittances. Marital status was divided into 5 categories, with the married as the reference group. Age was taken in years (15–64). We also included age squared for non-linearity.

2.4. Estimation Strategy

2.4.1. Logistic Model

In the first phase of the analysis, we sought to analyse how climate change affects the likelihood of being employed versus unemployed using a logistic model. the logistics models are useful in appreciating the probabilities of being unemployed as a result of climate change. In this case, the use of a logistic approach allows us to determine whether climate change has an impact on an individual's employment probability. We predict probabilities for male and female sub-models. The underlying latent variable model is specified as follows:

$$U^* = X'\beta + \mu \tag{13}$$

with the variables defined as previously discussed. The logistic estimator of the probability $p = \Pr(U = 1|X)$ is $\Lambda(X'\beta) = \frac{e^{X'\beta}}{1+e^{X'\beta}}$.

2.4.2. Ordered Logit

We employed ordered logit models to analyse the probabilities of being fully employed given unemployment and underemployment. This technique assumes that the predicted outcomes can be presented in categories or levels, allowing us to appreciate the effects on full employment relative to other labour market outcomes. The outcomes are of an ordered manner conditional on which are less or more likely to occur. Following [54], the labour market outcome variable in terms of hours supplied (HW) is categorised into the unemployed ($HW = 0$); the underemployed ($1 \leq HW \geq 26$) and fully employed ($HW > 27$).

Going from the latent variable model of Equation (15), our latent variable U^* is divided into m ordinal categories with two cut points (α_{m-1} and α_m), where $m = 3$.

$$U_i = \begin{cases} 1 \Rightarrow unemployed\ if \alpha_0 = -\infty \leq U^* < \alpha_1 \\ 2 \Rightarrow underemployed\ if\ \alpha_1 \leq U^* < \alpha_2 \\ 3 \Rightarrow fully\ employed\ if\ \ U^* \geq \alpha_2 \end{cases} \tag{14}$$

The probability that $U = m$, for given values of Xs equivalent to the region of the distribution where $\alpha_{m-1} \leq U^* < \alpha_m$ is: $\Pr(U = m|X) = \Pr(\alpha_{m-1} \leq U^* \langle \alpha_m|X) = F(\alpha_m - X\beta) - F(\alpha_{m-1} - X\beta)$, where F is the cumulative density function of μ.

2.4.3. Count Data and Selection Modelling

The logit and ordered logit models do not consider the importance of selection bias. To account for the full structure in terms of hours worked, we used a count data model. Count data modelling presents the outcomes in absolute numbers. These outcomes are given as countable amounts as opposed to as rank. In this case, the hours supplied includes zero hours for the unemployed. From the test of overdispersion, the negative binomial regression model is found to be more suitable than the Poisson counterpart.

In addition to this and for robustness, we also estimate a full selection model using the Heckman regression. The model corrects bias arising from non-random nature of self-selection to employment. The first equation centers on selection into the sample. It thus reflects the sample selection outcome (y_i^*). The second regression is the main equation of association between the various variables and the outcome. This reflects the selection predisposition (s_i^*). This can be estimated as:

$$\left.\begin{array}{l} y_i^* = x_i'\beta + \mu_i \\ s_i^* = z_i'\gamma + v_i \end{array}\right\} \tag{15}$$

where y_i^* and s_i^* are unobserved continuous variables, x_i' and z_i' are vectors of independent variables, β is the fundamental parameter vector of interest and μ_i and v_i denote the normally distributed error terms. X is presumed to be a subset of z. Thus, factors which forecast the principal outcome y, also forecast the selection propensity s. The outcome variables are observed if the latent selection propensity exceeds 0: $s_i = \begin{pmatrix} 1\ if\ s_i^* > 0 \\ 0\ if\ s_i^* \leq 0 \end{pmatrix}$.

2.4.4. Analysis by Sectors: Multinomial Logit

In addition to affecting labour supply, demand and intensity of employment, climate change may also alter the structure of employment. It is plausible that climate change may cause labour expansion in certain sectors and contractions in others as we conjectured earlier. The employment data are also observed at sectoral level. For this purpose, we employed a multinomial model (MNLM) to analyse the probability of being employed in a given sector and the role of climate change in these probabilities. The MNLM is characterised by a dependent variable with various categories which are conditional on multiple independent factors. The resultant multiple outcomes are not ordered. In this study the employment sectors were classified into 7 nominal categories: (1) Agriculture, hunting, mining and quarrying, (2) Private households, (3) Manufacturing, (4) Electricity, gas, water and construction, (5) Wholesale and retail trade, (6) Financial intermediation services, and (7) Community, social and personal services. The MNLM in this case is specified as follows:

$$p = \Pr(U = 1|X) \text{ is } p_{ij} = \frac{exp\left(X_i'\beta_j\right)}{\sum_l^m exp\left(X_i'\beta_l\right)},\ j = 1, \ldots, 7 \tag{16}$$

$$0 < p_{ij} < 1 \text{ and } \sum_{j=1}^m p_{ij} = 1$$

The base category is set to be the unemployed. The coefficients of all the other outcomes are interpreted relative to the unemployed category.

3. Results

We begin this section with the presentation of the descriptive statistics, then the estimation results. In the latter, the findings are presented in the order discussed in the estimation strategy, beginning with the results of the logistic models and concluding with the results of the MNLM.

3.1. Descriptive Statistics

Table 1 shows the descriptive statistics for the various variables in terms of the mean and standard deviations. For the period of study (2008 to 2017), there is on average 0.41 standard deviation of temperatures from the long-run mean. Standard deviations are in absolute values. Breaking the changes into positive and negative changes show that for this period, there has been 0.25-degree increase from the long-run mean, and 0.07 degrees decrease from the long-run mean on average. There were on average 2.18 heatwave days per year and a drought index of 34.21 for the females. The unemployment rate in our sample indicates more unemployment in the female subsample (35%) compared to males (25%). Of the employed, females worked on average 37.4 h a week and males offered 40.9 h a week. In general, the descriptive statistics show more unemployment and underemployment among the females compared to the males.

Table 1. Descriptive statistics.

Variables	Female		Male	
	Mean	**Sd**	**Mean**	**Sd**
Tdev.	0.41	0.05	0.41	0.05
Rdev.	106.64	45.26	103.93	45.28
Tdev.+	0.25	0.24	0.25	0.24
Tdev.−	−0.07	0.13	−0.07	0.13
Hwave	2.18	2.06	2.15	2.06
Drought	34.21	27.36	35.32	27.92
Age	33.19	12.83	31.28	12.53
Nlinc	2291.58	7084.58	2043.91	3574.23
Empl==Unemployed	0.35	0.48	0.25	0.43
Empl==Employed	0.65	0.48	0.75	0.43
Undeemp==unemployed	0.44	0.50	0.32	0.47
Undeemp==underemployed	0.10	0.30	0.07	0.26
Undeemp==fulltime	0.46	0.50	0.61	0.49
hw0	21.74	22.32	29.24	23.47
hw	37.41	16.79	40.91	17.56
sector==agriculture, hunting, fo	0.09	0.29	0.16	0.37
sector==Private households	0.17	0.38	0.03	0.16
sector==Mining and Quarrying	0.01	0.10	0.06	0.24
sector==Manufacturing	0.08	0.27	0.13	0.33
sector==Electricity, gas and wat	0.02	0.14	0.08	0.28
sector==Construction	0.02	0.13	0.09	0.29
sector==Wholesale and Retail tra	0.19	0.39	0.15	0.36
sector==Financial intermediation	0.07	0.26	0.08	0.27
sector==Community, social and pe	0.35	0.48	0.21	0.41
educat==no schooling	0.12	0.33	0.08	0.28
educat==incomplete primary	0.14	0.35	0.14	0.35
educat==complete primary	0.07	0.25	0.08	0.27
educat==incomplete secondary	0.40	0.49	0.42	0.49
educat==complete secondary	0.14	0.35	0.16	0.36
educat==national technical &cert	0.02	0.15	0.03	0.18
educat==post-sec certificate & d	0.08	0.27	0.07	0.26
educat==degree	0.02	0.14	0.02	0.14
loc==traditional	0.43	0.50	0.38	0.49
loc==Urban	0.51	0.50	0.53	0.50
loc==Farm	0.06	0.24	0.08	0.27
loc ru==Rural	0.49	0.50	0.47	0.50
loc ru==Urban	0.51	0.50	0.53	0.50
marstat==Married	0.24	0.43	0.26	0.44
marstat==Cohabiting	0.07	0.26	0.08	0.28
marstat==widow/widower	0.13	0.33	0.02	0.16
marstat==divorced/separated	0.03	0.16	0.02	0.13
marstat==never married	0.54	0.50	0.61	0.49
empsec==unemployed	0.44	0.50	0.31	0.46
empsec==agric. hunting, mining & quary~g	0.06	0.23	0.15	0.36
empsec==private households	0.10	0.30	0.02	0.14
empsec==manufacturing	0.05	0.21	0.09	0.28
empsec==elec. gas, water & construction	0.02	0.14	0.12	0.33
empsec==wholesale & retail trade	0.11	0.31	0.10	0.31
empsec==financial. Services	0.04	0.20	0.05	0.23
empsec==community, services	0.19	0.40	0.14	0.35
N	7026		10,656	

Note: HW0 is hours worked per week including the unemployed with zero hours, while HW captures hours work for the employed only. Sector captures sectors of employment for the employed, while the variable empsec includes the unemployed.

3.2. Estimation Results

The results of the estimations are presented according to the estimation strategies explained above. We first present the results of the logit models for the probabilities of being employed against being unemployed. Under the normal logit models, we also present the graphs of the changes in marginal effects by variation of climate change variables according to gender. The normal logit models are followed by the ordered logit models for the probabilities of being fully employed, given underemployment and unemployment. Following this, we present the results of the count data models, specifically the results of the negative binomial regressions, and a full selection analysis based on the Heckman regression model. The results of sectoral analyses performed using multinomial regressions are then presented.

3.2.1. Logistic Model

The logit model estimates the probabilities and odds of being employed relative to not being employed. The estimates are provided for female and male sub-models. For both Table 2a,b, columns 1 and 2 are results for average temperature deviation from long-run mean (Tdev.) and average rainfall from long-run mean (Rdev.). Columns 3 and 4 show results for positive and negative temperature deviations (Tdev.+ and Tdev.−) and extreme climate events (Hwave and Drought). Table 2a provides results of marginal effects. The findings show that temperature deviation has a negative sign for both males and females. Rainfall indicators have a magnitude close to zero for both females and males. The various education levels have different magnitudes and signs for females and males. Higher educational attainment tends to be associated with increasing probabilities of being employed. Similarly, marital status indicators reflect variations in magnitude and sign. Age, however, has a positive sign across the board.

Table 2. Logit model for probability of being employed.

(a) ME				
Variables	**(1) Female**	**(2) Male**	**(3) Female**	**(4) Male**
Tdev.	−0.116 *	−0.210 ***		
	(0.061)	(0.050)		
Rdev.	0.000 ***	−0.000 **		
	(0.000)	(0.000)		
Tdev.+			0.084 ***	−0.038 **
			(0.020)	(0.016)
Tdev.−			−0.057 *	0.081 ***
			(0.031)	(0.025)
Hwave			−0.008 ***	−0.002
			(0.002)	(0.001)
Drought			−0.001 ***	0.000
			(0.000)	(0.000)
Female				
Inc. primary	−0.038 *	−0.035 **	−0.042 *	−0.034 **
	(0.022)	(0.016)	(0.022)	(0.016)
Comp. primary	−0.004	−0.037 **	−0.009	−0.033 *
	(0.024)	(0.018)	(0.024)	(0.018)
Inc. secondary	−0.031	−0.028 **	−0.037 *	−0.024 *
	(0.020)	(0.014)	(0.020)	(0.015)
Comp. secondary	0.035 *	−0.014	0.030	−0.011
	(0.021)	(0.015)	(0.021)	(0.015)
Nat. technical & cert.	0.024	−0.006	0.018	−0.003
	(0.026)	(0.018)	(0.026)	(0.018)

Table 2. *Cont.*

(a) ME				
Variables	**(1) Female**	**(2) Male**	**(3) Female**	**(4) Male**
Post-sec cert. & dipl.	0.099 ***	0.015	0.093 ***	0.018
	(0.021)	(0.015)	(0.020)	(0.016)
Degree	0.162 ***	0.074 ***	0.157 ***	0.077 ***
	(0.021)	(0.016)	(0.021)	(0.017)
Age	0.028 ***	0.020 ***	0.028 ***	0.020 ***
	(0.002)	(0.002)	(0.002)	(0.002)
Age sq	−0.000 ***	−0.000 ***	−0.000 ***	−0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Nlinc	−0.000	−0.000 ***	−0.000	−0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Urban	0.038 ***	0.015 **	0.028 ***	0.017 ***
	(0.007)	(0.006)	(0.007)	(0.006)
Co-habiting	−0.032 **	−0.003	−0.029 **	−0.003
	(0.014)	(0.009)	(0.014)	(0.009)
Widow/Widower	0.108 ***	0.031 *	0.106 ***	0.029
	(0.016)	(0.018)	(0.016)	(0.018)
Divorced/Separated	0.116 ***	0.027 *	0.117 ***	0.026 *
	(0.019)	(0.015)	(0.019)	(0.016)
Never married	0.052 ***	−0.093 ***	0.053 ***	−0.095 ***
	(0.009)	(0.008)	(0.009)	(0.008)
Observations	14,930	13,707	14,930	13,707

(b) Odds Ratios				
Variables	**(1) Female**	**(2) Male**	**(3) Female**	**(4) Male**
Tdev.	0.47 *	0.13 ***		
	(0.19)	(0.06)		
F.##*Tdev.				
Rdev.	1.00 ***	1.00 **		
	(0.00)	(0.00)		
F.##Rdev.				
Tdev.+			1.73 ***	0.69 **
			(0.23)	(0.11)
F.## Tdev.+				
Tdev.−			0.69 *	2.19 ***
			(0.14)	(0.54)
F.##Tdev.−				
Hwave			0.95 ***	0.98
			(0.01)	(0.01)
F.##Hwave				
Drought			1.00 ***	1.00
			(0.00)	(0.00)
F.##Drought				
F.				
Inc. Primary	0.81	0.72 **	0.79 *	0.73 *
	(0.10)	(0.11)	(0.10)	(0.12)
Comp. Primary	0.98	0.71 **	0.95	0.73 *
	(0.14)	(0.12)	(0.14)	(0.13)
Inc. Secondary	0.84	0.76 *	0.81 *	0.79
	(0.10)	(0.11)	(0.10)	(0.12)
Comp. Secondary	1.25 *	0.87	1.22	0.90
	(0.16)	(0.14)	(0.16)	(0.14)
Nat. Tech. & Cert.	1.17	0.94	1.12	0.97
	(0.19)	(0.18)	(0.18)	(0.18)

Table 2. *Cont.*

(b) Odds Ratios				
Variables	**(1) Female**	**(2) Male**	**(3) Female**	**(4) Male**
Post-Sec Cert.& D..	2.11 ***	1.19	2.04 ***	1.23
	(0.29)	(0.20)	(0.28)	(0.21)
Degree	5.10 ***	3.70 ***	4.98 ***	3.80 ***
	(1.18)	(1.28)	(1.16)	(1.31)
Age	1.20 ***	1.22 ***	1.20 ***	1.21 ***
	(0.02)	(0.02)	(0.02)	(0.02)
Age sq	1.00 ***	1.00 ***	1.00 ***	1.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)
Nlinc	1.00	1.00 ***	1.00	1.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)
Urban	1.28 ***	1.15 **	1.20 ***	1.18 ***
	(0.06)	(0.06)	(0.05)	(0.06)
Co-habiting	0.84 **	0.97	0.85 **	0.96
	(0.06)	(0.11)	(0.06)	(0.11)
Widow/Widower	2.16 ***	1.72	2.12 ***	1.68
	(0.30)	(0.68)	(0.29)	(0.66)
Div./Sep.	2.34 ***	1.58	2.37 ***	1.55
	(0.42)	(0.50)	(0.42)	(0.49)
Never Married	1.38 ***	0.41 ***	1.39 ***	0.40 ***
	(0.08)	(0.04)	(0.08)	(0.04)
Constant	0.03 ***	0.81	0.03 ***	0.37 ***
	(0.01)	(0.30)	(0.01)	(0.12)
OBSERVATIONS	14,930	13,707	14,930	13,707

Note: Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The odds ratios of the logistics models are presented in Table 2b. The odds ratios are equally significant and the same significance levels as the predicted probabilities. The temperature deviation indicators show a higher magnitude for females than males, for higher temperatures. On the contrary, lower temperature deviations have a lower magnitude for females than for males. Heatwaves have a magnitude lower than 1 for both females and males. The drought indicator is however 1 for both females and males. The control variables such as urban location and age all have magnitudes greater than 1. In relation to education and marital status, in general the variables present higher magnitudes for the higher levels of education, and amongst the widowed and the divorced/separated, respectively.

Logistic regression results do not compute marginal effects for interaction models. This explains why we estimated separate female and male models. However, ref. [55], developed the user-written program for plotting the marginal effects of continuous variables, using the marginscontplot (mcp) command. We have used this command to generate the comparative marginal effects for males and females reported in Figure 1. The plotted marginal effects are from the estimations of the full sample. The effects reflect the average marginal effects reported earlier for the different gender sub-samples.

3.2.2. Ordered Logit

The ordered logit models consider not only employment status but the intensity of employment in terms of hours supplied. As with the logistics tables columns 1 and 2 give results for temperature deviation and columns 3 and 4 give results for asymmetric effects and extreme weather events.

The ordered logit models are presented in Table 3a for probabilities of being fully employed and 3b for associated odds ratios. Tables A1 and A2 in the Appendix A show the predicted probabilities of under-employment and unemployment, respectively. The standard temperature deviation is negative for both female and males, with a higher magnitude for males. Higher temperature deviation has a negative sign for males and a positive one for females. The magnitude of the impact of drought and heatwave are zero (0) and close to zero (0), for both sexes. Non-labour income has a negative sign with magnitude close to zero (0) across the board.

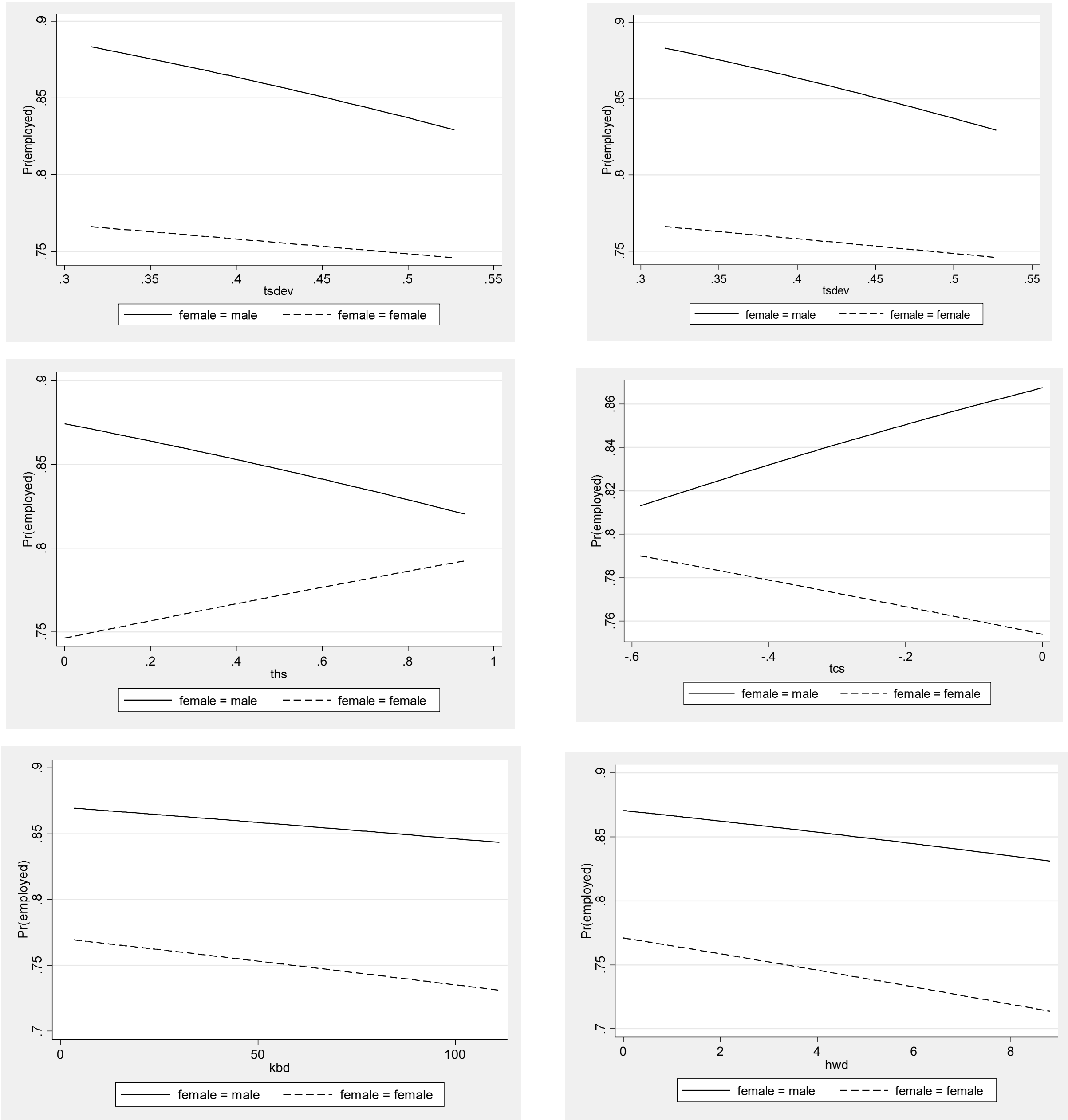

Figure 1. Graphs of marginal effects of climate shocks by gender. Note: tsdev is standard deviation of temperature; tdev is deviation of each temperature point from the long-run mean (LRM); this is the gap of a given temperature point above the LRM, tcs is the gap of a given temperature point below the LRM.

As illustrated in Table 3b, for standard temperature deviation the odds of being fully employed has a magnitude less than 1 for both female and males. For rainfall deviation however, the magnitude is close to one for both. For drought the magnitude is 1 specifically for the males. As before, the control variables continue to show variations in the magnitude. For instance, for both females and males, in general higher levels of education are associated with higher odds of being fully employed. Regarding marital status the tendency is not as clear cut, depending on the specific category.

Table 3. Ordered logit model.

(a) Predicted Probabilities of Full Employment				
Variables	**(1) Female**	**(2) Male**	**(3) Female**	**(4) Male**
Tdev.	−0.277 ***	−0.386 ***		
	(0.088)	(0.083)		
Rdev.	0.000 ***	−0.000 ***		
	(0.000)	(0.000)		
Tdev.+			0.023	−0.187 ***
			(0.028)	(0.026)
Tdev.−			−0.070	0.186 ***
			(0.045)	(0.042)
Hwave			−0.011 ***	−0.005 **
			(0.003)	(0.002)
*Drought			−0.000 **	0.000 **
			(0.000)	(0.000)
Female				
Inc. primary	−0.001	−0.030	−0.005	−0.021
	(0.026)	(0.025)	(0.026)	(0.026)
Comp. primary	0.045	−0.062 **	0.040	−0.050 *
	(0.029)	(0.029)	(0.029)	(0.029)
Inc. secondary	0.015	−0.026	0.011	−0.013
	(0.025)	(0.023)	(0.025)	(0.023)
Comp. secondary	0.156 ***	0.029	0.153 ***	0.040 *
	(0.026)	(0.024)	(0.026)	(0.024)
Nat. technical & cert.	0.160 ***	0.040	0.156 ***	0.049 *
	(0.033)	(0.029)	(0.033)	(0.029)
Post-sec cert. & dipl.	0.259 ***	0.076 ***	0.255 ***	0.086 ***
	(0.026)	(0.024)	(0.026)	(0.025)
Degree	0.354 ***	0.163 ***	0.352 ***	0.169 ***
	(0.029)	(0.028)	(0.029)	(0.029)
Age	0.059 ***	0.042 ***	0.059 ***	0.041 ***
	(0.003)	(0.003)	(0.003)	(0.003)
Age sq	−0.001 ***	−0.001 ***	−0.001 ***	−0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Nlinc	−0.000	−0.000 ***	−0.000	−0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Urban	0.074 ***	0.030 ***	0.062 ***	0.031 ***
	(0.010)	(0.010)	(0.010)	(0.009)
Co-habiting	−0.014	−0.015	−0.011	−0.017
	(0.017)	(0.014)	(0.017)	(0.014)
Widow/Widower	0.079 ***	−0.012	0.075 ***	−0.013
	(0.022)	(0.037)	(0.022)	(0.036)
Divorced/Separated	0.150 ***	0.015	0.151 ***	0.008
	(0.027)	(0.029)	(0.027)	(0.030)
Never married	0.088 ***	−0.155 ***	0.089 ***	−0.156 ***
	(0.013)	(0.013)	(0.012)	(0.012)
Observations	11,847	10,522	11,847	10,522
(b) Odds of Being Fully Employment				
Variables	**(1) Female**	**(2) Male**	**(3) Female**	**(4) Male**
Tdev.	0.318 ***	0.132 ***		
	(0.115)	(0.058)		
Rdev.	1.002 ***	0.998 ***		
	(0.000)	(0.001)		
Tdev.+			1.100	0.374 ***
			(0.127)	(0.050)
Tdev.−			0.747	2.661 ***
			(0.138)	(0.591)

Table 3. *Cont.*

(b) Odds of Being Fully Employment				
Variables	**(1) Female**	**(2) Male**	**(3) Female**	**(4) Male**
Hwave			0.957 ***	0.973 **
			(0.011)	(0.012)
*Drought			0.998 **	1.002 **
			(0.001)	(0.001)
F.				
Inc. primary	0.996	0.861	0.980	0.900
	(0.105)	(0.108)	(0.103)	(0.114)
Comp. primary	1.196	0.742 **	1.174	0.789 *
	(0.141)	(0.103)	(0.138)	(0.110)
Inc. secondary	1.061	0.880	1.043	0.936
	(0.104)	(0.102)	(0.103)	(0.109)
Comp. secondary	1.892 ***	1.167	1.875 ***	1.238 *
	(0.200)	(0.143)	(0.198)	(0.153)
Nat. technical & cert.	1.925 ***	1.241	1.900 ***	1.299 *
	(0.266)	(0.190)	(0.263)	(0.200)
Post-sec cert. & dipl.	3.074 ***	1.539 ***	3.026 ***	1.621 ***
	(0.334)	(0.204)	(0.329)	(0.215)
Degree	5.511 ***	3.132 ***	5.488 ***	3.199 ***
	(0.865)	(0.694)	(0.863)	(0.710)
Age	1.278 ***	1.244 ***	1.277 ***	1.241 ***
	(0.017)	(0.018)	(0.017)	(0.018)
Age sq	0.998 ***	0.997 ***	0.998 ***	0.997 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Nlinc	1.000	1.000 ***	1.000	1.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Urban	1.356 ***	1.169 ***	1.292 ***	1.174 ***
	(0.057)	(0.057)	(0.053)	(0.057)
Co-habiting	0.946	0.907	0.956	0.895
	(0.066)	(0.081)	(0.067)	(0.080)
Widow/Widower	1.383 ***	0.923	1.362 ***	0.916
	(0.129)	(0.216)	(0.127)	(0.215)
Divorced/Separated	1.896 ***	1.110	1.899 ***	1.058
	(0.238)	(0.232)	(0.238)	(0.221)
Never married	1.440 ***	0.437 ***	1.442 ***	0.432 ***
	(0.074)	(0.031)	(0.074)	(0.031)
/cut1	125.172 ***	3.016 ***	143.841 ***	6.075 ***
	(38.067)	(1.046)	(38.552)	(1.810)
/cut2	233.715 ***	5.143 ***	268.602 ***	10.391 ***
	(71.304)	(1.786)	(72.297)	(3.100)
Observations	11,847	10,522	11,847	10,522

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.2.3. Count Data and Selection Modelling of Hours of Labour Supplied

It is worth noting though that the findings so far may be plagued by selection bias that should be corrected. The first approach we take is to treat hours worked, ranging from 0 h for the unemployed to maximum hours, as count data. Therefore, the first model we estimate is the negative binomial (NB) regressions. The histograms in Figure 2 show evidence of overdispersion, which is later confirmed in the NB regressions by the overdispersion test parameters.

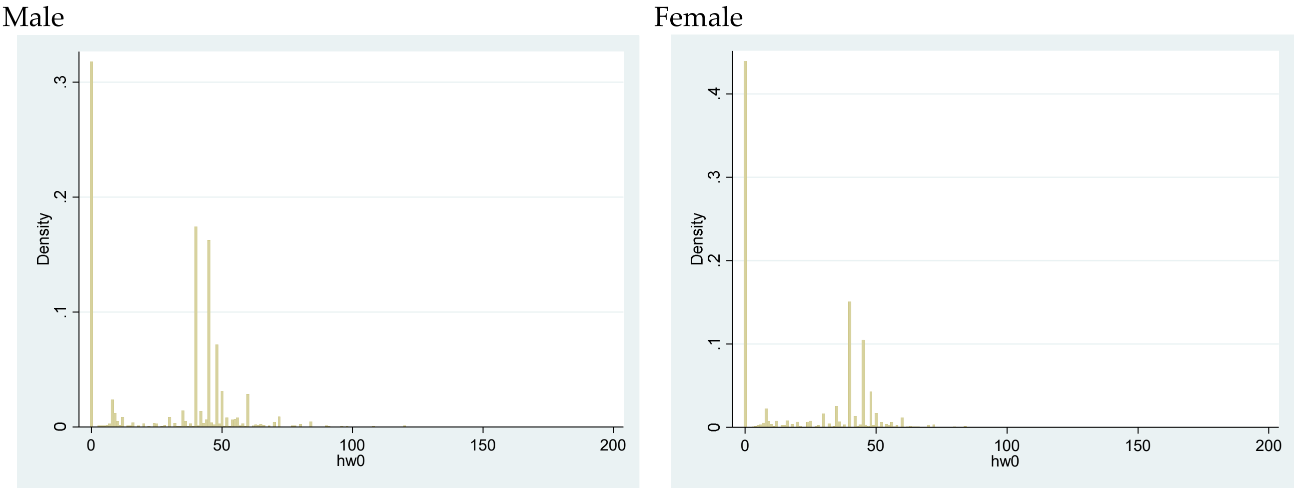

Figure 2. Histograms of hours worked per week by gender.

Correcting for this bias shows evidence of significant gender differences in the effects of climate variables on hours supplied to the disfavour of females. The negative binomial regression results are presented in Table 4. Climate change variables for males and females are in columns 1 and 2, and weather shocks similarly in columns 3 and 4. The standard temperature deviation for hours worked has a negative sign for both females and males. The magnitude, however, is higher for females than males. The positive temperature variation is negative for both females and males. The magnitude is much higher and significant for males but insignificant for females. The heat wave indicator is for both sexes but insignificant for the males.

Table 4. Negative binomial regression of hours worked—Marginal effects.

Variables	(1) Female	(2) Male	(3) Female	(4) Male
Tdev.	−16.728 **	−15.923 **		
	(6.988)	(7.564)		
Rdev.	0.013	−0.020 **		
	(0.009)	(0.009)		
Tdev.+			−1.187	−10.898 ***
			(2.257)	(2.397)
Tdev.−			−1.593	9.835 ***
			(3.454)	(3.700)
Hwave			−0.461 **	−0.307
			(0.214)	(0.222)
*Drought			−0.018	0.020
			(0.014)	(0.014)
F.				
Inc. primary	−0.756	−1.768	−0.853	−1.149
	(1.966)	(2.151)	(1.973)	(2.115)
Comp. primary	0.727	−2.860	0.594	−2.175
	(2.203)	(2.366)	(2.208)	(2.335)
Inc. secondary	−0.730	−1.818	−0.858	−1.091
	(1.832)	(2.016)	(1.839)	(1.979)
Comp. secondary	5.002 **	0.113	4.886 **	0.809
	(2.028)	(2.136)	(2.036)	(2.104)
Nat. technical & cert.	4.533 *	1.646	4.474 *	2.194
	(2.683)	(2.632)	(2.691)	(2.598)
Post−sec cert. & dipl.	7.893 ***	2.321	7.751 ***	2.944
	(2.097)	(2.284)	(2.104)	(2.251)

Table 4. *Cont.*

Variables	(1) Female	(2) Male	(3) Female	(4) Male
Degree	9.025 ***	2.367	9.008 ***	2.746
	(2.767)	(3.014)	(2.780)	(2.971)
Age	2.975 ***	2.380 ***	2.956 ***	2.357 ***
	(0.262)	(0.268)	(0.262)	(0.267)
Age sq	−0.032 ***	−0.029 ***	−0.032 ***	−0.028 ***
	(0.003)	(0.004)	(0.003)	(0.003)
Nlinc	−0.000	−0.000 ***	−0.000	−0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Urban	2.641 ***	0.573	2.243 ***	0.663
	(0.797)	(0.851)	(0.786)	(0.838)
Co−habiting	0.465	1.216	0.521	0.964
	(1.268)	(1.492)	(1.270)	(1.486)
Widow/Widower	3.999 **	0.977	3.762 **	0.831
	(1.847)	(4.044)	(1.829)	(4.028)
Divorced/Separated	4.572 **	1.667	4.497 **	1.256
	(2.163)	(3.217)	(2.157)	(3.183)
Never married	4.082 ***	−4.914 ***	4.079 ***	−5.048 ***
	(0.933)	(1.143)	(0.930)	(1.140)
/lnalpha	0.795 ***	0.272 ***	0.794 ***	0.269 ***
	(0.015)	(0.015)	(0.014)	(0.015)
Alpha	2.213 ***	1.313 ***	2.213 ***	1.309 ***
	(0.032)	(0.020)	(0.032)	(0.020)
Pr > Ch2	0.000	0.000	0.000	0.000
Observations	11,847	10,522	11,847	10,522

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The Heckman model which analyses a full selection process is reported in Table 5. We used the more robust two-step approach, also known as the Heckman-type correction for self-selection model. The latter acts as a control model. It does not require the restriction of variables. Instead, the model's underlying assumption is that of the normality of the errors. It allows for the straightforward testing for endogeneity through the inclusion of a term in the second stage. One standard deviation increase in temperature results in 7.86 less hours worked for females. The effect on males is not significant. The coefficient of selection indicates that a standard deviation in temperature results in less likelihood of employment for males than females.

Table 5. Heckman selection models: hours supplied given self-selection to employment.

	(1)	(2)	(3)	(4)
Variables	HW Female	Empl Female	HW Male	Empl Male
Tdev.	−7.855 **	−0.486 *	3.146	−1.298 ***
	(3.227)	(0.249)	(3.671)	(0.292)
Rdev.	−0.003	0.001 ***	−0.006	−0.001 ***
	(0.004)	(0.000)	(0.004)	(0.000)
Inc. primary	1.100	−0.110	1.266	−0.248 ***
	(0.968)	(0.078)	(0.935)	(0.088)
Comp. primary	1.055	0.029	0.317	−0.250 **
	(1.048)	(0.086)	(1.050)	(0.098)
Inc. secondary	1.617 *	−0.061	0.578	−0.201 **
	(0.902)	(0.073)	(0.854)	(0.082)
Comp. secondary	3.866 ***	0.289 ***	0.022	0.013
	(1.000)	(0.077)	(0.862)	(0.086)

Table 5. *Cont.*

	(1)	(2)	(3)	(4)
Variables	**HW Female**	**Empl Female**	**HW Male**	**Empl Male**
Nat. technical & cert.	5.187 ***	0.211 **	2.211 **	−0.007
	(1.198)	(0.097)	(1.038)	(0.106)
Post-sec cert. & dipl.	4.762 ***	0.623 ***	−0.056	0.197 **
	(1.190)	(0.080)	(0.940)	(0.093)
Degree	5.334 ***	1.083 ***	−2.473 *	0.756 ***
	(1.478)	(0.120)	(1.282)	(0.164)
Age	0.621 **	0.150 ***	−0.243	0.152 ***
	(0.302)	(0.009)	(0.265)	(0.010)
Age sq	−0.007 **	−0.001 ***	0.002	−0.002 ***
	(0.003)	(0.000)	(0.003)	(0.000)
Nlinc	0.000	−0.000	0.000 ***	−0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Urban	0.362	0.207 ***	−1.633 ***	0.126 ***
	(0.493)	(0.029)	(0.406)	(0.033)
Co-habiting	2.335 ***	−0.066	−0.161	−0.017
	(0.677)	(0.047)	(0.550)	(0.062)
Widow/Widower	1.654 *	0.437 ***	−0.669	0.205
	(0.898)	(0.076)	(1.462)	(0.189)
Divorced/Separated	3.581 ***	0.460 ***	0.819	0.168
	(0.945)	(0.094)	(1.141)	(0.153)
Never married	2.618 ***	0.247 ***	−0.073	−0.561 ***
	(0.553)	(0.035)	(0.815)	(0.049)
Lambda		7.317 **		−4.877
		(3.364)		(3.836)
F.				
Constant	22.367 ***	−3.166 ***	50.030 ***	−0.853 ***
	(8.572)	(0.208)	(5.269)	(0.232)
Observations	11,847	11,847	10,521	10,521

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.2.4. Analysis of Effects of Climate Change in Economic Sectors—Multinomial Logit

Given the importance of understanding the transformations in sectoral dynamics as a result of the effect of climate shocks we undertook to analyse the odds of employment by sector for both females and males. The purpose of this analysis is to bring out any structural shifts in sectoral employment due to climate change. The results of the multinomial logit regressions which provides for the comparison of outcomes based on the log odds are presented in Table 6a,b for male and female subsamples, respectively.

According to the results of the male sample estimates in Table 6a, there are five key broad sectors in which climate change significantly and negatively affects male employment. These are agriculture, hunting, mining and quarrying (AHMQ), Manufacturing (MAN), Financial intermediation (FIN), Electricity, gas water and construction (EGWC) and wholesale and retail trade (WRT). The female subsample estimates in Table 6b show three sectors in which climate change leads to significant shedding of female jobs. These are AHMQ, WRT and MAN.

Table 6. Multinomial logit of employment by sectors.

(a) Male Subsample							
Variables	**(2) Agric, Hunting Mining and Quarrying**	**(3) Private House-Holds**	**(4) Manufacturing**	**(5) Elec. Gas Water and Construction**	**(6) Wholesale Retail Trade**	**(7) Financial Interm. Services**	**(8) Community Social Pers. Service**
Tdev.	0.02 ***	1.28	0.01 ***	0.09 ***	0.28 *	0.03 ***	3.08
	(0.01)	(1.72)	(0.01)	(0.06)	(0.20)	(0.03)	(2.15)
Rdev.	0.99 ***	0.99 ***	1.00 ***	1.00	1.00 *	1.00 ***	1.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Inc. primary	0.48 ***	0.49 ***	0.81	0.93	0.60 *	1.66	1.01
	(0.08)	(0.13)	(0.21)	(0.20)	(0.16)	(0.94)	(0.25)
Comp. primary	0.39 ***	0.40 ***	0.78	0.98	0.88	2.63 *	1.17
	(0.08)	(0.13)	(0.22)	(0.24)	(0.25)	(1.51)	(0.32)
Inc. secondary	0.29 ***	0.31 ***	1.22	1.21	1.16	4.53 ***	1.36
	(0.05)	(0.08)	(0.29)	(0.25)	(0.28)	(2.39)	(0.32)
Comp. secondary	0.20 ***	0.17 ***	1.59 *	1.37	2.06 ***	7.98 ***	4.28 ***
	(0.04)	(0.06)	(0.39)	(0.30)	(0.51)	(4.25)	(1.02)
Nat. technical & cert.	0.32 ***	0.17 ***	1.23	1.32	1.70 *	13.60 ***	2.62 ***
	(0.07)	(0.09)	(0.36)	(0.34)	(0.48)	(7.45)	(0.73)
Post-sec cert. & dipl.	0.22 ***	0.13 ***	1.69 **	1.46	2.05 ***	17.82 ***	9.49 ***
	(0.05)	(0.06)	(0.44)	(0.34)	(0.54)	(9.57)	(2.34)
Degree	0.71	0.00	3.09 **	2.06	2.37 *	51.66 ***	47.14 ***
	(0.30)	(0.00)	(1.39)	(0.91)	(1.10)	(32.60)	(18.70)
Age	1.33 ***	1.25 ***	1.26 ***	1.28 ***	1.26 ***	1.36 ***	1.46 ***
	(0.03)	(0.06)	(0.03)	(0.03)	(0.03)	(0.05)	(0.04)
Age_sq	1.00 ***	1.00 ***	1.00 ***	1.00 ***	1.00 ***	1.00 ***	1.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nlinc	1.00 ***	1.00 ***	1.00 ***	1.00 ***	1.00 ***	1.00 ***	1.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Urban	0.42 ***	1.01	2.09 ***	1.67 ***	2.13 ***	1.85 ***	1.50 ***
	(0.03)	(0.15)	(0.19)	(0.13)	(0.18)	(0.20)	(0.12)
Co-habiting	1.11	1.65 **	0.80	1.02	0.88	1.10	0.67 ***
	(0.15)	(0.38)	(0.12)	(0.15)	(0.13)	(0.20)	(0.10)
Widow/Widower	1.50	2.67 *	1.43	1.58	1.15	2.37	1.71
	(0.65)	(1.49)	(0.69)	(0.71)	(0.59)	(1.24)	(0.74)
Divorced/Separated	1.43	2.47 *	1.79	1.72	1.43	1.21	1.25
	(0.52)	(1.32)	(0.66)	(0.62)	(0.55)	(0.53)	(0.45)
Never married	0.32 ***	0.66 **	0.30 ***	0.42 ***	0.37 ***	0.47 ***	0.34 ***
	(0.04)	(0.14)	(0.04)	(0.05)	(0.04)	(0.07)	(0.04)
Constant	0.79	0.01 ***	0.06 ***	0.03 ***	0.02 ***	0.00 ***	0.00 ***
	(0.42)	(0.02)	(0.04)	(0.01)	(0.01)	(0.00)	(0.00)
Observations	10,656	10,656	10,656	10,656	10,656	10,656	10,656
(b) Female Subsample							
Variables	**(2) Agric, Hunting Mining and Quarrying**	**(3) Private House-Holds**	**(4) Manufac-turing**	**(5) Elec. Gas Water and Construction**	**(6) Wholesale Retail Trade**	**(7) Financial Interm. Services**	**(8) Community Social Pers. Service**
Tdev.	0.0008 ***	0.97	0.21 *	0.44	0.11 ***	0.53	12.93 ***
	(0.00)	(0.63)	(0.17)	(0.49)	(0.07)	(0.46)	(7.15)
Rdev.	1.00 **	1.00 ***	1.01 ***	1.00	1.00	1.00	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Inc. primary	0.74 *	0.96	1.00	0.52 **	1.13	0.83	0.81
	(0.13)	(0.16)	(0.25)	(0.17)	(0.32)	(0.32)	(0.16)
Comp. primary	0.78	1.17	1.30	0.55	1.40	1.02	1.36
	(0.15)	(0.21)	(0.36)	(0.21)	(0.42)	(0.43)	(0.29)
Inc. secondary	0.32 ***	0.80	1.39	0.73	2.34 ***	1.16	1.81 ***
	(0.05)	(0.13)	(0.33)	(0.21)	(0.61)	(0.41)	(0.32)
Comp. sec.	0.20 ***	0.60 ***	2.12 ***	1.39	5.36 ***	3.54 ***	5.25 ***
	(0.04)	(0.11)	(0.53)	(0.42)	(1.41)	(1.27)	(0.97)
Nat. tech. and cert.	0.34 ***	0.36 ***	0.73	0.74	3.01 ***	5.63 ***	6.16 ***
	(0.09)	(0.10)	(0.27)	(0.32)	(0.90)	(2.16)	(1.34)
Post-sec cert. and dipl.	0.28 ***	0.24 ***	1.65 *	1.91 **	5.30 ***	7.43 ***	17.78 ***
	(0.06)	(0.06)	(0.44)	(0.59)	(1.43)	(2.68)	(3.33)
Degree	0.63	0.13 ***	2.00	4.54 ***	4.38 ***	18.65 ***	56.09 ***
	(0.26)	(0.10)	(0.88)	(1.92)	(1.66)	(7.83)	(15.08)
Age	1.21 ***	1.52 ***	1.27 ***	1.29 ***	1.27 ***	1.29 ***	1.29 ***
	(0.03)	(0.04)	(0.04)	(0.06)	(0.03)	(0.04)	(0.03)
age_sq	1.00 ***	1.00 ***	1.00 ***	1.00 ***	1.00 ***	1.00 ***	1.00 ***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Nlinc	1.00 ***	1.00 ***	1.00	1.00	1.00	1.00	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Urban	0.37 ***	1.70 ***	1.89 ***	1.19	2.34 ***	3.83 ***	1.19 ***
	(0.03)	(0.13)	(0.18)	(0.15)	(0.17)	(0.48)	(0.08)
Co-habiting	1.37 **	0.89	1.02	0.86	0.88	0.85	0.61 ***
	(0.18)	(0.11)	(0.16)	(0.19)	(0.11)	(0.15)	(0.07)

Table 6. *Cont.*

(b) Female Subsample							
Variables	**(2) Agric, Hunting Mining and Quarrying**	**(3) Private House-Holds**	**(4) Manufac-turing**	**(5) Elec. Gas Water and Construction**	**(6) Wholesale Retail Trade**	**(7) Financial Interm. Services**	**(8) Community Social Pers. Service**
Widow/Widower	1.57 **	2.69 ***	2.17 ***	2.13 **	2.52 ***	2.22 ***	2.28 ***
	(0.35)	(0.45)	(0.49)	(0.63)	(0.49)	(0.56)	(0.37)
Divorced/Separated	3.12 ***	2.28 ***	3.06 ***	2.24 **	2.42 ***	2.94 ***	1.81 ***
	(0.85)	(0.50)	(0.78)	(0.77)	(0.55)	(0.75)	(0.37)
Never married	1.77 ***	1.97 ***	1.82 ***	1.51 ***	1.67 ***	1.39 ***	1.18 **
	(0.20)	(0.18)	(0.21)	(0.23)	(0.14)	(0.16)	(0.09)
Constant	0.22 **	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***	0.00 ***
	(0.14)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	11,942	11,942	11,942	11,942	11,942	11,942	11,942

Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4. Discussion

The findings presented in the previous section will be discussed here. Following the previous pattern, we will discuss the findings in the order presented above, starting with the logistic models and ending with the MNLM.

4.1. Logistic Models

The theoretical basis of labour market modelling in this case postulates several control variables included in the model. Judging from the log likelihood Chi2 values which are consistently above 1000 and the respective probabilities of 0.0000, we judge the logistic models to have performed well. These control variables have the expected signs and significance levels. For example, in Table 2a the different categories of education suggest that possessing incomplete primary education is significantly associated with less probability of being employed. However, completed secondary education and having a degree increase the probability of employment significantly and the probabilities rise with rising levels of education. This is line with previous expectations [50]. Non-labour income is associated with less probability of being employed. This is in concordance with previous findings [49]. However, the coefficient is very weak, in tandem with the fact that majority of South Africans earn their living from the labour market. In line with economic theory, we also find that staying in urban locations is associated with higher probability of being employed.

In line with our a priori expectations [47,51], the variables capturing climate change and climatic events indeed show that climate change has a negative effect on the labour market. As illustrated in Table 2b, the magnitudes of the odds ratios for the standard temperature deviation are less than one. This implies the lesser odds of being employed as a result of temperature deviations from the mean. One standard deviation increase in temperature is associated with 0.47 times more employment relative to unemployment for females and 0.13 for males. That is, the lesser the odds of being employed due to climate change for males than for females. This finding is contrary to our expectations. As previously discussed, with the occurrence of climate change and climate shocks, we expected to find evidence of more and more women being unemployed compared to their male counterparts due to the nature of their social responsibilities [33,34,36,38,39]. Nonetheless, this could be as a result of adaptation strategies and change in gender roles which result in females taking greater workloads [46]. The rainfall variable is significant, but the magnitude is close to zero. Climate scientists have therefore rightfully focused on temperature. Going forward we will focus our analyses on temperature.

The predicted probabilities of temperature deviations are negative and significant at 10% level for females and 1% level for males. One standard deviation of average annual temperatures from its long-run mean results in 0.12 and 0.21 less probabilities of being employed for female and male sub-samples, respectively (Table 2a). The odds ratios are equally significant and the same significance levels as the predicted probabilities (Table 2a).

In line with our priori expectations, our findings suggest evidence of asymmetric effects of climate change. Positive temperature deviations have different effects on employment than negative deviations. The models that deal with asymmetry have also controlled for extreme weather events, precisely heat wave and drought. Given that most of the effects of climate change on humans will be captured through extreme weather events, it is therefore expected that the asymmetric effects will be weaker. Positive temperature changes after controlling for extreme weather events increase the probability of being employed for females. One standard deviation increase in temperatures results in 0.8 increase in probability of being employed for females and 0.04 decrease in the probability of being employed for males. One standard deviation reduction in temperature results in 0.06 probability of less employment for females and 0.08 probability of more employment for males. The heatwaves and droughts significantly reduce the probability of being employed among females (by 0.008 and 0.001 points, respectively), but not significantly so for males. Overall, when temperature changes are considered together with the extreme climate events, the picture is that of significantly more negative impact on female employment than on male employment. The values of marginal effects in Table 2b are also in line with these probabilities. Notably, we expected to find some level of asymmetric effects of climate change and climate shocks as discussed previously. Nevertheless, we had no prior expectations of the engendered differences specific to the various climate variables.

The probability of being employed falls with increase in standard deviation in temperatures (Figure 1). In line with the analyses above, the falls in marginal effects are steeper for males than females. The asymmetric effects under the gender effects are also evident on the 3rd and 4th graphs of the figure. Extreme weather events have somewhat steeper effects for females than males. Our take from the logistic models is that climate change reduces the probability of being employed, but it is the occurrence of extreme weather events that widens the gap between male and female employment in disfavour of females.

4.2. Ordered Logit

The Chi2 and the respective probabilities also suggest well-specified models. The different control variables also behave in line with the theoretical expectations. The models show that one standard deviation in temperature reduces the probability of full employment by 0.28 for females and 0.39 for males. Correspondingly, the same unit change in the climate variable increases the probability of under-employment by 0.05 for females and 0.10 for males (Table A2 in the Appendix A). As before, increases in standard deviation temperature increase the probability of full employment by 0.19 for males; however, declines in the variable increase probability of full employment by 0.19 also. The effects are the opposite for females but not significant. Heat waves and drought occurrences significantly reduce the probability of full employment for females more than for males. The predicted probabilities of underemployment reflect this interpretation as well. The odds ratios are equally in line with these interpretations (Table 3b). This is in line with previous findings that indicate that, in the face of climatic shocks, females will sacrifice their time in search of fuels for the upkeep of the household [34].

4.3. Count Data and Selection Modelling of Hours of Labour Supplied

Correcting for selection bias shows evidence of significant gender differences in the effects of climate variables on hours supplied to the disfavour of females. The likelihood ratio tests and the standard errors of alpha relative to the coefficients suggest over dispersion which justifies our choice for negative binomial regression over the Poisson model. The results suggest that the effect of climate change in terms of temperature deviation from its long-run mean is significantly biased against females. One standard deviation rise in temperature results in 16.73 less hours worked for females compared to 15.92 less hours worked for males (Table 4).

As presented in Table 5, the coefficients of lambda, rho and sigma suggest significant evidence of selection bias. The estimates confirm a significant bias in the effect of climate change against female labour supply. One standard deviation increase in temperature results in 7.86 less hours worked for females. The effect on males is not significant. The coefficient of selection indicates that a standard deviation in temperature results in less likelihood of employment for males than females. What we observe from the selection modelling is that climate change significantly reduces the probability of being employed more for males than females, which is consistent with the findings of the logistic models. However, the effect of climate change is manifested in less hours supplied for females as opposed to the likelihood of being employed. The latter supports the findings which indicate that, due to their inherent social responsibilities, women tend to be time-poor; therefore, they face a high economic cost of their time usage [39].

4.4. Analysis of Effects of Climate Change in Economic Sectors—Multinomial Logit

The estimates along gender lines show evidence of significant bias in the climate-induced structural change. In agriculture, hunting, mining and quarrying sector, one standard deviation increase in temperature results in 0.02 times more likelihood of employment for males, but the odds are 0.0008 for females. This means that the sector sheds far more female jobs due to climate change than males. It is therefore in this sector that climate change perpetuates gender inequality in the labour market. The findings are line with previous studies. As indicated in prior discussions, females in South Africa are still overly predisposed to climate change in comparison to males, in part due to the engendered division of labour [36]. The one single sector that tends to significantly expand female employment due to climate change is the community, social and personal services (CSPS). A standard deviation rise in temperature results in 12.93 times more female employment in this sector relative to the unemployed.

It is worth noting that although the private household (PH), and the community, social and personal services (CSPS) sectors show tendencies of male employment increases following climate change, none of these are significant. The PH sector is generally characterised by hospitality industry, where guesthouse, cookery and some tourism-related jobs are classified [56]. The CSPS sector comprises among others, health and care services. We establish therefore, that as the climate changes, significant negative health effects might ensue, resulting in more frailty and need for more health and care services. These services are generally better provided by female workers, hence, the significant expansion of the sector for females. The significant deindustrialisation resulting from climate change affects both males and females alike. This means that the policy channel through which climate change might affect employment, especially due to policy-induced changes in technologies are not properly exploited in South Africa. Policy should be encouraged to promote the green economy and hence green jobs. Attention must also be paid to the tourism and hospitality sector which shows some potential, though at the moment insignificantly, to absorb male labour that may be shed from other sectors due to climate change.

5. Conclusions

Increasing climatic events and South Africa's exposure to extreme weather events, coupled with high and increasing unemployment, prompted us to examine the climate change–labour market nexus and its gender effects. We specifically focused on the role of climate change and climatic shocks on unemployment; under-employment; employment intensity; and possible climate-induced structural changes in employment patterns. We applied logistics, ordered logit, count data, selection models, and multinomial logit models using district municipality-level climate data and extreme weather events to match individual-level employment information in two-yearly waves from 2008 to 2016/2017.

Climate change in terms of standard deviation of average annual temperatures from its long-run mean and extreme weather events such as heatwaves and droughts result in less probability of being employed. However, when temperature changes are considered together with the extreme climate events, the picture is that of significantly more negative impact on female employment than on male employment. Our take from the logistic models is that climate change reduces the probability of being employed, but it is the occurrence of extreme weather events that widens the gap between male and female employment to the disfavour of females. We also reached a similar conclusion with the probabilities of full employment. Controlling for selection effects in count data and Heckman modelling brings to light a clear gender bias in climate change. The selection modelling reveals that climate change significantly reduces the probability of being employed more for males than females. This is consistent with the findings of the logistic models. However, the effect of climate change is manifested in less hours supplied for females as opposed to the likelihood of being employed.

Sectoral analysis shows that the most employment contraction due to climate change is observed in the agriculture and manufacturing sectors. The sectors are also associated with more female job-shedding than males. The disaggregation by sectors suggests that all other productive sectors tend to contract due to climate change, but the community, social and personnel services (CSPS) tend to expand significantly. The expansion in the CSPS sector is mostly female jobs. It has been posited that climate change may have a significant effect on health. The CSPS sector comprises among others, health and care services. We establish, therefore, that as the climate changes, significant negative health effects might ensue, resulting in more frailty and need for more health and care services. These services are generally better provided by female workers, hence the significant expansion of the sector for females. Another sector that shows a tendency for expansion (of mostly male jobs) is the personal and household services sector. This sector is generally characterised by hospitality industry, where guesthouse-, cookery- and some tourism-related jobs are classified [56]. Notably, the significant deindustrialisation resulting from climate change affects both males and females alike. This means that the policy channel through which climate change might affect employment, especially due to policy-induced changes in technologies, is not properly exploited in South Africa. Policy must be encouraged to expand employment opportunities by promoting the green economy and hence green jobs. Attention must also be paid to the tourism and hospitality sector which shows some potential, though at the moment insignificantly, to absorb male labour that may be shed from other sectors due to climate change.

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Appendix A

Table A1. Ordered logit model—Predicted probabilities of unemployment.

Variables	(1) Female	(2) Male	(3) Female	(4) Male
Tdev.	0.225 ***	0.283 ***		
	(0.071)	(0.061)		
Rdev.	−0.000 ***	0.000 ***		
	(0.000)	(0.000)		
Tdev.+			−0.019	0.136 ***
			(0.023)	(0.019)
Tdev.−			0.057	−0.136 ***
			(0.036)	(0.031)
Hwave			0.009 ***	0.004 **
			(0.002)	(0.002)
*Drought			0.000 **	−0.000 **
			(0.000)	(0.000)
F.				
Inc. primary	0.001	0.023	0.005	0.016
	(0.024)	(0.019)	(0.024)	(0.019)
Comp. primary	−0.040	0.048 **	−0.036	0.038 *
	(0.027)	(0.022)	(0.027)	(0.022)
Inc. secondary	−0.013	0.019	−0.010	0.010
	(0.023)	(0.017)	(0.023)	(0.017)
Comp. secondary	−0.132 ***	−0.021	−0.129 ***	−0.030 *
	(0.023)	(0.017)	(0.023)	(0.018)
Nat. technical & cert.	−0.135 ***	−0.029	−0.132 ***	−0.036 *
	(0.028)	(0.021)	(0.028)	(0.021)
Post-sec cert. & dipl.	−0.207 ***	−0.054 ***	−0.204 ***	−0.061 ***
	(0.023)	(0.018)	(0.023)	(0.018)
Degree	−0.270 ***	−0.113 ***	−0.268 ***	−0.117 ***
	(0.024)	(0.020)	(0.024)	(0.020)
Age	−0.048 ***	−0.031 ***	−0.048 ***	−0.030 ***
	(0.003)	(0.002)	(0.003)	(0.002)
Age sq	0.000 ***	0.000 ***	0.000 ***	0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Nlinc	0.000	0.000 ***	0.000	0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Urban	−0.061 ***	−0.022 ***	−0.051 ***	−0.023 ***
	(0.009)	(0.007)	(0.008)	(0.007)
Co-habiting	0.012	0.010	0.010	0.012
	(0.015)	(0.010)	(0.015)	(0.009)
Widow/Widower	−0.066 ***	0.008	−0.063 ***	0.009
	(0.018)	(0.025)	(0.018)	(0.025)
Divorced/Separated	−0.120 ***	−0.010	−0.120 ***	−0.006
	(0.020)	(0.020)	(0.020)	(0.020)
Never married	−0.073 ***	0.114 ***	−0.073 ***	0.114 ***
	(0.011)	(0.009)	(0.010)	(0.009)
Observations	11,847	10,522	11,847	10,522

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A2. Ordered logit model—Predicted probabilities of under-employment.

Variables	(1) Female	(2) Male	(3) Female	(4) Male
Tdev.	0.051 ***	0.103 ***		
	(0.016)	(0.022)		
Rdev.	−0.000 ***	0.000 ***		
	(0.000)	(0.000)		
Tdev.+			−0.004	0.050 ***
			(0.005)	(0.007)
Tdev.−			0.013	−0.050 ***
			(0.008)	(0.011)
Hwave			0.002 ***	0.001 **
			(0.001)	(0.001)
*Drought			0.000 **	−0.000 **
			(0.000)	(0.000)
F.				
Inc. primary	0.000	0.008	0.000	0.005
	(0.002)	(0.006)	(0.002)	(0.006)
Comp. primary	−0.004	0.015 **	−0.004	0.012 *
	(0.003)	(0.007)	(0.003)	(0.007)
Inc. secondary	−0.001	0.006	−0.001	0.003
	(0.002)	(0.006)	(0.002)	(0.006)
Comp. secondary	−0.024 ***	−0.008	−0.024 ***	−0.011 *
	(0.003)	(0.006)	(0.003)	(0.006)
Nat. technical & cert.	−0.025 ***	−0.011	−0.025 ***	−0.013 *
	(0.006)	(0.008)	(0.006)	(0.008)
Post-sec cert. & dipl.	−0.052 ***	−0.021 ***	−0.051 ***	−0.024 ***
	(0.004)	(0.007)	(0.004)	(0.007)
Degree	−0.084 ***	−0.051 ***	−0.084 ***	−0.052 ***
	(0.007)	(0.009)	(0.007)	(0.009)
Age	−0.011 ***	−0.011 ***	−0.011 ***	−0.011 ***
	(0.001)	(0.001)	(0.001)	(0.001)
Age sq	0.000 ***	0.000 ***	0.000 ***	0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Nlinc	0.000	0.000 ***	0.000	0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)
Urban	−0.013 ***	−0.008 ***	−0.011 ***	−0.008 ***
	(0.002)	(0.003)	(0.002)	(0.002)
Co-habiting	0.002	0.005	0.001	0.005
	(0.002)	(0.004)	(0.002)	(0.004)
Widow/Widower	−0.013 ***	0.004	−0.013 ***	0.004
	(0.004)	(0.011)	(0.004)	(0.011)
Divorced/Separated	−0.030 ***	−0.005	−0.030 ***	−0.003
	(0.007)	(0.009)	(0.007)	(0.010)
Never married	−0.015 ***	0.041 ***	−0.015 ***	0.042 ***
	(0.002)	(0.004)	(0.002)	(0.004)
Observations	11,847	10,522	11,847	10,522

Standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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