The Role of Reservation Wages in Youth Unemployment in Cape Town, South Africa: A Structural Approach*

James Levinsohn
Yale University

Todd Pugatch
University of Michigan

May 7, 2010

Abstract

We examine the role of reservation wages in youth unemployment in South Africa by estimating a structural job search model with survey data on the reservation wage. We find that inclusion of reservation wage data implies a labor market in which job offers are relatively frequent but at wages that tend to be too low to be accepted. Using a novel procedure, we combine our structural estimates with reservation wage survey data to estimate the full distribution of search costs in the sample. These estimates confirm the model's predictions about the relationship between search costs and labor market outcomes, thereby allowing for insights into individual-specific heterogeneity in structural parameters that may not be inferred from the observed data alone. Counterfactual simulation of an employer wage subsidy predicts an increase in reservation wages, but also an increase in accepted wages and a decreased probability of experiencing a lengthy unemployment spell. To our knowledge, this is the first attempt to apply survey data on reservation wages to a structurally estimated search model for a developing country.

*Corresponding author: Todd Pugatch, Department of Economics, Lorch Hall, 611 Tappan Street, Ann Arbor MI 48103; tpugatch@umich.edu. We thank Justin McCrary for his essential input as a co-author on previous versions of this paper. Cally Ardington, Nicola Branson, David Lam, and Jessica Goldberg oriented us to CAPS and graciously shared their programs for formatting the data. Brian McCall provided invaluable guidance on the structural estimation techniques used in this paper. David Lam, Murray Leibbrandt, Zoë McLaren, Jeffrey Smith, Kevin Stange, Martin Wittenberg, and seminar participants at the University of Michigan, the University of Cape Town, Centre for European Economic Research (ZEW), NEUDC, and 5th IZA/World Bank Conference on Employment and Development provided useful comments.

1 Introduction

Unemployment is persistently high in South Africa, and has increased dramatically since the fall of apartheid. According to the standard International Labor Organization (ILO) definition, national unemployment among 16-64 year olds rose from 15.6 percent in 1995 to 26.7 percent in 2005. Using a broader definition, unemployment rose from 28.2 percent to 41.1 percent over the same period.[1] Youths are particularly likely to be unemployed: using the ILO definition, in 2005 the unemployment rate for 16-19 year olds was 56.6 percent, while for 20-24 year olds it was 52.3 percent. These rates far exceed those in developed countries such as the United States, as shown by the trends in employment/population ratios among 15-24 year olds shown in Figure 1. The immediate causes of such trends in unemployment are found largely in the substantial increases in labor force participation since the fall of apartheid, which has occurred for almost all groups but particularly among African women. The new entrants tended to be less skilled than those already in the labor force. At the same time that labor supply was increasing, labor demand stagnated, particularly for the low-skilled (Banerjee et al, 2007).

Despite broad agreement on these proximate causes of the unemployment increase, its level and persistence remain a puzzle. Standard labor market models would predict that wages should decline to clear the market and reduce unemployment to more reasonable levels than those observed. Although there is evidence that real incomes have fallen since apartheid (Leibbrandt, Levinsohn and McCrary, 2005), the failure of unemployment rates to fall frustrates conventional economic wisdom. The observed patterns suggest that there are substantial frictions in the labor market. One hypothesis regarding such frictions is

[1] The ILO definition classifies "working age individuals as being in the labor force if during a week of reference they were employed or wanted to work and were available to start working within a week but also had actively looked for work during the past four weeks...The broader definition...[eliminates] the requirement of having actively searched for a job in order for an individual as to be classified as unemployed." (Banerjee et al, 2007: 6).

that reservation wages among the unemployed are high relative to offered wages, leading job searchers to reject job offers as unacceptable (or leading firms to adapt by failing to make such offers in the first place). According to this reservation wage hypothesis, the fall of apartheid spurred a climate of increased economic expectations among previously disenfranchised groups, particularly blacks and coloureds. Such heightened labor market expectations for disadvantaged groups coincided with increased human capital investments, resulting in reservation wages that tended to exceed employers' willingness to pay. Thus the reservation wage hypothesis holds that the increase in South African unemployment is largely voluntary, resulting from an influx of workers unwilling to work for the prevailing wages offered by firms.

In this paper, we examine the reservation wage hypothesis by estimating a structural job search model applied to the Cape Area Panel Study (CAPS), a panel dataset of youth in Cape Town with detailed histories of education, job search and labor market behavior. The structural search approach is appropriate for the context we study because it explicitly models the labor market frictions that lead to equilibrium unemployment and estimates their magnitude. As is well known, the structural approach also provides a valid framework in which to conduct policy simulations, making our results more useful for policymakers seeking to reduce South African unemployment. Although estimation of a structural search model can not determine whether reservation wages are "too high," as the reservation wage hypothesis contends, it can nonetheless determine what must be true of the model's parameters in order to reconcile the observed data, thereby offering a picture of the labor market consistent with a search model in which agents follow a reservation wage policy.

The data we use are particularly suited to our purpose since they focus on a group (urban youth) with extremely high unemployment rates, and contain survey reports of the reservation wage, which is typically unobserved. We estimate the parameters of a simple search model with survey data on reservation wages, which allows us to assess the role of reservation wages under the restrictions implied by our model. To our knowledge, this is the first attempt to apply data on reservation wages from a developing country to a structurally estimated search model, and among a handful of studies in the broader job search literature that use survey measures of reservation wages. Our model incorporates measurement error in reported wages and observed heterogeneity in the structural parameters, and makes use of survey data on reservation wages in a novel procedure to recover the full distribution of net search costs in the sample. For comparative purposes, we also estimate our model using alternate reservation wage measures that could be obtained in the absence of survey reports.

We find that inclusion of reservation wage data as an input to our model implies a labor market in which job offers are relatively frequent but at wages that tend to be too low to be accepted, in stark contrast to results obtained using the traditional method of estimating reservation wages from the accepted wage distribution or by maximum likelihood, which imply less frequent offers that are accepted with higher probability. Using the model's results to estimate individual-specific net search costs provides insights on individual heterogeneity relevant to search behavior, confirming the model's predictions about the relationship between search costs and labor market outcomes. Counterfactual policy simulation of an employer wage subsidy shows that youths increase their reservation wages in response to the subsidy, but by an amount modest enough for the subsidy to both increase accepted wages and reduce the probability of lengthy unemployment spells.

To use the terminology of Eckstein and van den Berg (2007), our model is a standard "classical job search" model. As such, it is a partial equilibrium model, in that it models only the worker's optimal search policy in a dynamic setting, leaving the firm's behavior as exogenous; and it is a "wage posting" model, in that firms post wages which potential workers must either accept or reject (in contrast to "bargaining" models, in which workers and firms bargain over the wage after a match has been made). Flinn and Heckman (1982) provide an extensive discussion of parameter identification in such models. Christensen and Kiefer (1991) present a model of this type that is quite similar to ours, develop its likelihood function, and discuss parameter identification. Our model follows Wolpin (1987) and Eckstein and Wolpin (1995) in its focus on the transition from school to work, and is among the small number of papers (such as Lancaster and Chesher (1983) Lynch (1984), and van den Berg (1990)) to use survey data on the reservation wage in a structurally estimated search model.

This paper also is part of a vast literature on unemployment in South Africa. For our purposes, the most relevant is the recent literature on search and reservation wages in Cape Town. Nattrass and Walker (2005) analyze data from the Khayelitsha/Mitchell's Plain (KMP) survey conducted in 2000-2001, which sampled working-age adults from a Cape Town working-class district. They use a reservation wage report similar to that used in this paper, and find that it is generally consistent with other reports of labor search behavior reported in the survey, with the vast majority reporting reservation wages below their predicted wages. They conclude that elevated reservation wages are not a major contributor to adult unemployment in this Cape Town district. Using the same KMP data, Schoer and Leibbrandt (2006) find that several different search strategies prevail in the data. They classify individuals as "non-searchers," "exclusive active searchers," "exclusive passive searchers" and "mixed strategy searchers," and find that observable characteristics have strong correlations with the choice of search strategy. Their results suggest that in Cape Town, search is not a monolithic activity, as most search models imply. We nonetheless model search as a simple process in this paper, though future work may attempt to differentiate between search strategies.

The remainder of the paper is structured as follows: the next section presents the model and discusses its estimation and identification. Section 3 describes the data and Section 4 presents results. Section 5 discusses results from estimation of search costs, and Section 6 presents results of the policy simulation of an employer wage subsidy. Section 7 concludes.

2 Model, Estimation and Identification

2.1 Model and Estimation

We consider the infinite-horizon dynamic programming problem of an unemployed worker searching for a job in continuous time, who faces a known wage offer distribution with cumulative distribution function $F_W(w)$ and Poisson job offer arrival rate q. When unemployed, the searcher's flow value of leisure[2] is b and she/he discounts the future by discount factor δ. If accepted, a job pays constant wage w, but the worker faces an exogenous probability of job separation p. Once rejected, wage offers may not be recalled. The corresponding continuous-time Bellman equations for the value of search and employment (V^s and V^e, respectively) are:

$$(1-\delta)V^s = b + qE[\max\{0, V^e(w') - V^s\}] \tag{1}$$

$$(1-\delta)V^e(w) = w + p[V^s - V^e(w)] \tag{2}$$

where w' denotes a future draw from F_W. The reservation wage w^* makes the agent indifferent between accepting the job offer and continued search, i.e., it solves: $V^e(w^*) = V^s$. Manipulation of the above Bellman equations lead to the following standard expression

[2]The flow value of leisure may also be viewed as the net search cost. In this paper, I will use the terms "flow value of leisure," "net search cost," and "search cost" interchangeably. All refer to the model parameter b.

for the reservation wage w^*:

$$w^* = b + \frac{q\delta}{(1-\delta)+p}\int_{w^*}^{\infty}(w-w^*)dF_W(w) \tag{3}$$

Policy function iteration for w^* may be conducted using the above.[3,4]

The model implies a joint distribution of accepted wages and unemployment durations, $f(w,d|w \geq w^*)$, which will form the basis of the likelihood function and whose parameters we seek to recover. Since the model assumes that offer arrivals are independent of wage draws, this joint distribution may be factored as the product of the marginal distributions of accepted wages and unemployment durations, leaving us with $f(w,d|w \geq w^*) = f_W(w|w \geq w^*) \times f_D(d|w \geq w^*)$. We consider estimation of each in turn.

According to the model, no agent accepts a wage below the reservation wage, allowing us to use the truncation of the wage distribution from below at w^* to recover the parameters of the wage offer distribution, since $f_W(w|w \geq w^*) = \frac{f_W(w)}{1-F_W(w)}$. In practice, however, wages are measured with error, so that some reported wages may fall below the reservation wage. Suppose classical measurement error, such that $w_o = w + \epsilon$, where w_o denotes observed wages and $\epsilon \sim N(0, \sigma_\epsilon^2)$ is independent of w. Although the support of the measurement error distribution is unbounded, we may bound realized draws of ϵ by noting that no true accepted wage may fall below w^*, i.e., $\Pr(w < w^*) = 0$.[5] Therefore we have:

[3] Note that as a partial equilibrium model, we do not model how firm behavior helps to determine F_W in equilibrium. Although this restricts the realism of the model, it allows us to maintain our focus on youth labor supply. Moreover, the leading method for structurally estimating a search model in general equilibrium, the Burdett-Mortensen model (as exemplified by Van Den Berg and Ridder, 1998) assumes wage offer and accepted wage densities that are increasing in the wage, which is squarely contradicted by our data.

[4] We also do not account for institutional features of the labor market such as minimum wages or union wage-setting. We feel this is justified because several studies have found low enforcement rates of minimum wages in South Africa (Hertz 2005, Yamada 2007, Dinkleman and Ranchhod 2010), and in the CAPS data, only 2% of employed respondents reported being union members (Wave 2). Youths facing these constraints in particular occupations should be able to switch sectors with relative ease.

[5] This approach to bounding the measurement error distribution follows Christensen and Kiefer (1994), although they do not assume that the measurement error is normally distributed, as we do.

$$\begin{aligned} w = w_o - \epsilon \geq w^* \Leftrightarrow \\ \epsilon \leq w_o - w^* \equiv \bar{\epsilon} \end{aligned} \tag{4}$$

The corresponding density of observed wages is:

$$f_W(w_o|w \geq w^*) = \int_{-\infty}^{\bar{\epsilon}} f_W(w_o|w \geq w^*, \epsilon)\phi\left(\frac{\epsilon}{\sigma_\epsilon}\right) d\epsilon \tag{5}$$

where $\phi(\cdot)$ is the standard normal density.[6]

Now consider the density of unemployment durations, $f_D(d)$. Under the assumption of Poisson offer arrivals, the hazard rate of unemployment exit, h, is a (constant) product of the offer arrival rate and the probability that a wage draw exceeds the reservation wage, i.e., $h = q(1 - F_W(w^*))$. Accordingly, unemployment durations are distributed exponentially with parameter h, so that $f_D(d) = h \exp(-hd)$. In practice, however, some unemployment spells will be right-censored, so that observed duration $d = \min\{d^*, d_c\}$, where d^* is the true duration and d_c is the duration observed when the spell was censored. Let $c = \mathbb{I}\{d = d_c\}$ be an indicator for censored spells. Then the density of observed unemployment durations, $g_D(d)$, is:

[6] Allowing instead for measurement error in reservation wages rather than accepted wages would not change the results of our model. To see this, suppose (without loss of generality) that reservation wages are measured with error, such that $w_o^* = w^* - \epsilon$, where w_o^* is the observed reservation wage and ϵ is distributed $N(0, \sigma_\epsilon^2)$, as above. Then we would have:

$$\begin{aligned} w \geq w^* = w_o^* + \epsilon \Leftrightarrow \\ w - w_o^* \equiv \bar{\epsilon} \geq \epsilon \end{aligned}$$

This leads to the same upper bound on ϵ, and thus the same accepted wage density as the case with measurement error in wages. The only difference would arise in the interpretation of the placement of the measurement error, but estimation results would be identical.

$$g_D(d) = f_D(d)^{1-c}[1 - F_D(d)]^c \tag{6}$$

We observe a sample of accepted wages and (possibly right-censored) unemployment durations. By definition, we do not observe accepted wages for those with right-censored durations, and an additional subset of observations with completed unemployment spells may also have missing wage data. Let $m = \{0, 1\}$ be an indicator for missing wage data. Therefore, the vector of observed data for each observation is $Y = (w, d, c, m)$, and the corresponding log likelihood function is:[7]

$$L(\theta|Y) = \sum_{i=1}^{N}(1 - m_i)\ln f_W(w_{o_i}|w_i \geq w^*; \theta) + \ln g_D(d_i; \theta) \tag{7}$$

We estimate (7) using quasi-Newton techniques, with starting values chosen from initial estimates obtained from separate, preliminary estimation of the observed wage and unemployment duration distributions. We parameterize the wage offer distribution as exponential with parameter λ, so that the model parameters estimated by the likelihood function are $\theta = (q, \lambda, \sigma_\epsilon)$.[8] We describe estimation of the reservation wage w^* in the following section.

2.2 Identification

Identification of the model parameters depends crucially on the reservation wage. In addition to determining the policy function of the theoretical search model, the reservation wage plays a key role in empirical parameter identification in the likelihood function. By providing the truncation point of the accepted wage distribution, the reservation wage,

[7] Appendix A describes the derivation and form of the likelihood function in greater detail.

[8] To restrict our estimated parameters to the positive domain, as implied by theory, we actually estimate each parameter as exponentiated functions of observable characteristics, e.g., $q = \exp(\phi' X)$. Note that the parameters (b, δ, p) of the theoretical model are not identified by the likelihood function.

in conjunction with the dispersion of accepted wages around it, serves to identify the underlying wage offer distribution. Additionally, its role in truncating the accepted wage distribution helps to identify the measurement error variance by placing an upper bound on the measurement error for all observed wages. Moreover, by entering into the expression for the hazard rate of unemployment exit, the reservation wage helps to identify the offer arrival rate by reconciling variation in observed unemployment durations with the probability of offer acceptance.

We estimate the preferred version of the model using survey data on the reservation wage, since the main purpose of this paper is to describe the South African youth labor market as implied by the reservation wage reports. Because the CAPS data we use in this paper has the rare advantage of survey reports of the reservation wage, we use the median reservation wage (within cells defined by included covariates) as model inputs. The median reservation wage, rather than individual reservation wage reports, is used because under the model all agents face identical structural parameters and therefore must have an identical reservation wage.[9]

However, for comparative purposes, we also estimate the model under alternative measures of the reservation wage, and report how results change under each. Under the model assumptions, the minimum accepted wage in the data is a consistent estimator of the reservation wage (Flinn and Heckman 1982). However, under the assumption that wages are measured with error, this estimator will be susceptible to outliers in the left tail of the observed wage distribution, so instead we use the 5th percentile of observed wages, which is also a consistent estimator of the reservation wage (Flinn and Heckman 1982, Eckstein and Van Den Berg 2007).[10]

[9] We could also choose the mean reservation wage or other measure of central tendency, but chose the median because it is less sensitive to outliers. Parameter estimates obtained using mean reservation wages are qualitatively similar to those obtained under the median.

[10] Flinn and Heckman (1982) and Eckstein and Van Den Berg (2007) note that any fixed order statistic

The theoretical model also provides a means to identify the reservation wage in a manner that is fully structural. However, in doing so, several problems arise. The first is the reliance of the reservation wage estimate on the calibration of several model parameters (in particular, b, δ, and p) which are not identified by the likelihood function alone. Moreover, as the truncation point of the accepted wage distribution, the reservation wage may not be estimated by maximum likelihood, because it is a boundary value. However, because our model assumes that measurement error in the reservation wage may lead some observed wages to fall below the reservation wage, the boundary value problem is eliminated, and the reservation wage may indeed be estimated as an additional model parameter in a conventional maximum likelihood framework.

3 Data

We use data from the Cape Area Panel Study (CAPS), a longitudinal study of youth in metropolitan Cape Town, South Africa. CAPS sampled about 4,800 youths aged 14-22 in Wave 1 (August-December 2002) and currently contains four waves, the most recent conducted in 2006. For our purposes, the most relevant features of the data are its monthly histories (for a period of 52 months from 2002-2006) of education, search and employment activity, as well as its questions on reservation wages. We focus only on those youths who have permanently left school,[11] are observed for at least 12 months in the calendar sample, and have a valid response to the reservation wage question. Additionally, those outside the 1st and 99th percentiles of the accepted wage distribution are dropped to limit the

of the accepted wage distribution consistently estimates w^*.

[11] We define school exit as being out of school for at least 3 consecutive months. In our sample, 6% report returning to school in at least one month after leaving school permanently according to our definition, but none of these have returned to school full-time (i.e., they always report searching or working concurrently with re-enrollment in school).

influence of outliers in the estimation.[12] This leaves $N = 1,430$ individuals in the sample. Key variables are described in Appendix B.

Table 1 presents summary statistics for the full sample. Among the notable features are the high durations and rates of unemployment: mean duration to first job since school exit is nearly 12 months, while 42% of the sample is unemployed for at least one year. Observed search behavior appears low: only 19% of the the time till first job (or censoring) is spent in search, and 35% report never searching since leaving school. Nonetheless, few youths are returning to school: only 6% report returning to school before obtaining their first job (or censoring), and none returned to school full-time (i.e., all report searching or working concurrently with re-enrollment in school). Of those who find work, most (77%) are employed full-time.[13]

Table 2 breaks down unemployment durations and rates by observable characteristics. The trends follow the expected patterns: unemployment is more prevalent and prolonged for coloureds and blacks, females, the young, and the low-skilled (both in terms of low schooling and low ability). The levels can be quite striking, however, even for the most advantaged groups: 21% of whites and 15% of those with at least some post-secondary education are unemployed for at least one year since school exit, for instance. Another surprising result is the post-school labor market experience of those who report never searching: of this group, only 36% are censored, meaning that the remaining 64% obtain a job, despite reporting to never have searched. This suggests that "search," at least as understood by the survey respondents, is not necessary to obtain employment, and thus many youths who may appear to be non-participants in the labor market may in fact be

[12] Estimation results using the untrimmed sample are qualitatively similar to those with trimming for most variants of the model. However, the model using maximum likelihood estimation of the reservation wage produces several coefficients with inconsistent sign using the untrimmed sample.

[13] Our model results are qualitatively similar when excluding part-time workers from the sample.

searching passively, or at least prepared to accept a job should an acceptable offer arrive.[14] Table 3, which shows how youths obtained their first job since school exit, provides more supporting evidence for the prevalence of passive search: more than 60% of the sample obtained their first job through informal networks.

Given the high prevalence and duration of unemployment in the sample, the question of what youths are doing with their time after leaving school naturally arises. Table 4 seeks to answer this question with data from more recent waves, for which the most post-school observations are available. Less than 1% are dead, suggesting fatal illnesses such as AIDS are not immediately afflicting this age group, although 7% do report serious illness. Although only 6% are married and 4% currently pregnant (including males who report their partners as pregnant), 18% are caring for their own children. A large percentage, 78%, remain co-resident with at least one parent, with 18% living in a household with a pensioner, suggesting that many youths may still have access to intra-household resource transfers. Less than 10% engage in unpaid work, suggesting that informal or underground employment does not explain the lack of wage employment in the sample.

Because reservation wage reports will be used in the main version of the model, it is worth pausing to consider the quality of the reservation wage data. Our reservation wage measure is the minimum monthly wage for which the youth reported to be willing to accept full-time work, measured at the latest wave prior to obtaining a job after permanent school exit (or censoring).[15] Table 1 shows that 24% of those with completed spells and non-missing wage data report reservation wages that exceed their reported wage; Figure 2 is a graphical depiction of the same, with points below the 45-degree line indicating

[14] Our definition of "never searched" excludes those who report obtaining employment immediately after leaving school. Although such youths do not report searching between school exit and employment, we expect that many in fact did actively search for work prior to obtaining work, and therefore exclude them from the "never searched" group so as not to bias results.

[15] Appendix B contains additional details on the construction of the reservation wage measure.

observations for which $w^* > w$. While this is troubling, the model can account for such discrepancies through its estimates of the distribution of measurement error in wages. Table 5 presents regressions of the reservation wage on a set of observable characteristics. Although few coefficients are statistically significant, they generally enter with the expected sign: reservation wages are lower among females, blacks and coloureds, who likely face more labor market disadvantages than similarly-skilled males and whites; lower (convexly) as a function of age, suggesting that older youths are less patient in their search; higher for the more skilled, as proxied by schooling and ability; higher for those with employed fathers or with co-resident parents, likely due to the greater availability of intra-household transfers; lower for those whose parents want them more strongly to work; and lower for those with their own children in the household, who have greater need to accept paid work. A notable exception is the negative coefficient on pension receipt by a household member, which contradicts the conventional wisdom that availability of pension-related resources increases reservation wages, although the coefficient is significant only at the 10% level. The regression results suggest that, despite some discrepancies between observed wages and reservation wages, the reservation wage data from the survey are generally internally consistent when considering correlations with observable attributes.

A major assumption of our model is the constant arrival rate of wage offers, which (in combination with the assumption that all other structural parameters are time-invariant) implies that the reservation wage is also constant. Given the high prevalence of observations for which the reservation wage report is inconsistent with search theory (i.e., for which $w^* > w$), it is reasonable to wonder whether the reservation wage declines over time. Because CAPS asks about reservation wages in each wave of the panel, we can test this hypothesis by regressing the reported reservation wage on unemployment duration. By including individual fixed effects, we can separate (time-invariant) unobserved heterogeneity from duration dependence; evidence of the latter, in the form of a negative coefficient on unemployment duration, would be evidence against our assumption of constant reservation wages. Table 7 presents results. Column (1), which restricts the sample to the first unemployment spell (following permanent school exit) only, has a positive but statistically insignificant coefficient on unemployment duration. Column (2) extends the sample to multiple spells, and finds a positive (and marginally significant) coefficient on unemployment duration. Thus we find no evidence that the reservation wage declines over the course of an unemployment spell, giving us confidence that our assumption of constant reservation wages is plausible.[16]

Finally, we consider the adequacy of our distributional assumptions used to form the likelihood function. Figures 3 and 4 show kernel density estimates of accepted wages and first unemployment spells, respectively; recall that both distributions are assumed exponential for purposes of estimation.[17] Although the empirical distributions from the full sample may mask considerable heterogeneity and thus can not show that our distributional assumptions are correct, observable patterns consistent with the exponential distribution (e.g., monotonically decreasing with a long right tail) will at least suggest that our estimates may fit the data well. The accepted wage distribution (Figure 3) does exhibit the left tail mode and long right tail that is characteristic of the exponential distribution; in our model, measurement error may account for the increasing density in the far left tail. The unemployment duration density (for completed spells; Figure 4) also exhibits these patterns, and appears to be consistent with our assumption of a constant hazard rate of

[16]Moreover, the leading methods for incorporating time-varying reservation wages in structurally estimated search models make unpalatable assumptions: assuming a finite search horizon (as in Wolpin (1987)) seems unsuited to youth seeking their first job following school exit, and allowing structural parameters (typically the unemployment benefit, as in Van Den Berg (1990)) to evolve over time in a known fashion does not seems at odds with the South African context.

[17]Under exponential wage offers, the density of accepted wages will also be exponential, with a rightward shift of the offer distribution by the amount of the reservation wage.

unemployment exit, in the aggregate.[18]

4 Results

4.1 Parameter Estimates

Table 8 presents estimates of our model, using the median reservation wage (within included covariate cell) from survey reports as the measure of w^*. Observed heterogeneity is incorporated by modeling (the natural log of) each parameter as a linear function of a parsimonious set of covariates: dummies for black, coloured, high school graduate, at least some college, high ability,[19] and previous work experience; the omitted group is low-ability whites with less than a high school education and no previous work experience. The reservation wage is calculated within groups defined by these covariates; for reference, Table 5 reports regressions of w^* and w_{q_5} on the covariates. The measurement error variance is estimated as a single parameter for the entire sample, however.[20]

Consider first the results for q, the job offer arrival rate: the "baseline level" reported in the first row is the exponentiated value of the constant term, and may be interpreted as the monthly probability of receiving a job offer for the omitted group.[21] The baseline monthly probability of a job offer is 27%. The reported coefficients on $\ln q$ represent the marginal effect, in log points, on the offer arrival rate. We see that blacks and coloureds face offer arrival rates that are .8 and .4 log points (or 80% and 40%) lower, respectively, than those for whites. High school graduation and post-secondary schooling generate large

[18] Although the kernel density is increasing in the far left tail, the empirical mode is 1 month (the minimum allowed, by assumption), so the empirical density does have its mode at the left tail of the distribution.

[19] We define "high ability" as above the median literacy and numeracy evaluation score within the estimation sample.

[20] Although in principle we could have treated the measurement error as heteroskedastic by allowing its variance to vary according to observable characteristics, in practice the measurement error coefficients were rarely significant in such models, and frequently led to numerical instability in the parameter estimates.

[21] When the estimate exceeds unity, the parameter may also be interpreted as the predicted number of job offers per month.

returns on offer arrivals (coefficients of .48 and .69, respectively), while high ability and previous work experience also increase the offer arrival rate considerably (coefficients of .27 and .37, respectively). The estimates imply that a black, low-ability high school dropout with no previous work experience has a monthly offer probability of just 12%, but that high ability, previous work experience and some college education nearly quadruple this probability, to 46%.

Now consider the results for λ, the wage offer distribution parameter, whose baseline represents the mean (and standard deviation) of the wage offer distribution; coefficients are marginal effects in log points, as before. The estimated baseline wage offer, at 710 rand, is quite low relative to the mean accepted wage of 2,486 rand.[22] Not surprisingly, the model predicts that only 29% of wage offers are accepted.[23] As with the offer arrival rate, the model estimates considerable labor market disadvantages for black and coloured youth (coefficients -.32 and -.13, respectively). Schooling, ability and previous work experience generate large returns, however, with the coefficient of .73 on previous work experience particularly notable (although this coefficient may be picking up a number of omitted factors that are correlated with experience, such as motivation or access to employment networks). Comparing model estimates again for black, low-ability high school dropouts with no previous work experience to their high ability, college-educated and experienced counterparts, we find that the former face a mean wage offer of 513 rand, while the latter receives offers more than four times as large, at 2,113 rand. The estimated measurement error standard deviation, σ_ϵ, implies that measurement error accounts for 27% of the standard deviation in accepted wages.[24]

[22] Such a comparison must be interpreted with caution, however, as the baseline wage offer is for the omitted category of white, low ability high school dropouts without previous work experience, while the mean accepted wage is for the full sample.

[23] We calculate the probability of offer acceptance, $\Pr(w \geq w^*)$, as the mean over the distribution of the full sample, i.e., $\Pr(w \geq w^*) = \int \Pr(w \geq w^*|x) f(x) dx$.

[24] Bound and Krueger (1991) found that measurement error accounts for 18% of the variance in reported

Table 9 repeats the estimates of Table 8, and presents parameter estimates for two additional models that vary by the reservation wage used in estimation (as indicated at the top of each column): w^* is the median reservation wage from survey reports; w_{q5} is the 5th percentile of accepted wages; and w^*_{MLE} leaves the reservation wage as a parameter to be estimated.[25] As in Table 7, the reported baseline represents the estimated level for each parameter for the omitted group, while the coefficients represent marginal effects, in log points. Results are qualitatively consistent regardless of the reservation wage used in estimation, with expected signs on all coefficients.

Turning first to results for q, the job offer arrival rate, we see that baseline offer arrivals are estimated to be more frequent under w^* than the other models: a monthly job offer probability of .27, versus .07 and .15 under w_{q5} and w^*_{MLE}, respectively. Although the differences between the models shrinks for some groups when coefficients are factored in, the generally higher offer arrival rates of column (1) are consistent with higher reservation wages under w^*: youth who face more frequent offers will be more choosy about which to accept.

Differences between the models' estimates of λ, the wage offer distribution parameter, are also quite striking. The baseline mean wage offer of 1,445 rand in the model with w_{q5} (Table 9, column 2) is more than double that of the model with w^*. The baseline offer of 899 rand in the model with w^*_{MLE} (column 3), while not nearly as high, still exceeds the baseline under w^* by more than 20%. Again, certain coefficients mitigate these differences somewhat, but the generally lower level of wage offers in the model with w^* comes through clearly in the estimated probabilities of offer acceptance: 29% under w^*, versus 59% and 44% under w_{q5} and w^*_{MLE}, respectively. Considered in conjunction with the offer arrival

annual earnings for men in the US.

[25] In the estimation, w^*_{MLE} is restricted to be $w^* = \bar{w} - \lambda$, corresponding to the truncation of the exponential accepted wage distribution at w^*.

rate results, the estimates offer a contrasting picture of the labor market: under w^*, wage offers are relatively frequent but low, while under w_{q_5} offers are infrequent but high.

This arrival/wage offer tradeoff is how the model reconciles different reservation wages using the same data on unemployment durations and accepted wages. Accordingly, the probability of offer acceptance ($\Pr(w \geq w^*)$) implied by the models suggest that if youths behave according to their reservation wage reports, they are less than half as likely to accept a wage offer than under w_{q_5}; we will return to this discrepancy and suggest possible explanations shortly. Results for the model with w^*_{MLE} fall somewhere in between the other two, with intermediate offer arrivals and wage offers for most subgroups, as may be expected when we "let the data speak" to find the best fit.

The estimated measurement error standard deviation, σ_ϵ, is greatest in the model with w^* and smallest in the model with w_{q_5}. This is unsurprising: recall that the measurement error parameter serves to reconcile the density of observed wages below the reservation wage, and hence should be largest in the model with w^*, since reservation wages are highest (on average) in that case. Finally, the coefficients on w^*_{MLE} in column (3) follow a qualitatively similar pattern to those on the alternative reservation wage measures presented in Table 5. As expected, black and coloured youth have lower reservation wages relative to whites, while reservation wages are increasing in schooling and ability. Interestingly, the negative coefficient on previous work experience suggests that youths who have already engaged in paid work are willing to work for less than their inexperienced peers, although this coefficient is imprecisely estimated.

The relatively frequent offer arrivals and low job acceptance probability in the model with w^* begs the question, "If the South African youth labor market is so bad, why are youths turning down so many jobs?" Our answer is that it is quite unlikely that youths are actually receiving, and refusing, job offers with the frequency implied by our estimates. Instead, we consider it more likely that low-wage jobs are more abundant than the unemployment data may suggest, but such low-wage matches are made infrequently. "Search" is not necessarily an active process for this group, as the 64% of our sample who obtained employment without ever reporting search activity suggests. Thus the high frequency of offer arrivals and refusals we estimate are more likely to represent "implicit refusals" of offers that youths know to be available, but are not literally made by a particular employer.

4.2 Model Fit

The structural search model generates predictions for the distributions of unemployment durations and accepted wages, and estimates of these distributions may be compared to their empirical counterparts to assess model fit. Before considering formal tests of model fit, we first offer a more qualitative assessment of how well our estimates account for some features of the data.

Consider first the distribution of unemployment durations till obtaining the first job. Because some durations are right-censored, it will be convenient to work with the survivor function for unemployment, or the probability that an unemployment spell d exceeds some value d_0 (i.e., $S(d_0) = \Pr(d \geq d_0)$). Table 10 shows, in column (1), the empirical survivor function at various monthly durations, along with model estimates according to the reservation wage value in columns (2)-(4). Perhaps the most noteworthy aspect of the results is that, beginning at a duration of 24 months, the predicted survivor function weakly exceeds its empirical counterpart for all estimated models. This means that youths are experiencing shorter unemployment spells than our model predicts at the right tail of the distribution.

Now consider the distribution of accepted wages. Recall that by incorporating measurement error in the reported wage, our model estimates the distribution of *observed* accepted wages, which is therefore directly comparable to empirically observed accepted wages. In Table 10, we compare this empirical distribution with its estimated counterparts at their respective means, standard deviations, and selected quantiles. All estimated models have mean and standard deviation that fall somewhat below those of the empirical distribution. The reported quantiles suggest that the reason may be the longer right tail of the empirical distribution: the 75th and 90th quantiles of all estimated models are below those of the empirical distribution, and such a longer right tail in the empirical distribution will increase its mean and standard deviation relative to the estimated models.

To test the model formally, we conduct both Pearson and LM tests separately for the unemployment duration and accepted wage distributions of each model.[26] We reject the null hypothesis that the model is correctly specified in all cases. Moreover, no model appears to offer an unambiguously better fit than the others, leaving no clear reason to favor one method of measuring reservation wages over another.

5 Search Cost Estimation

The model estimation described in preceding sections used values for the reservation wage defined within each covariate cell; thus, all coloured high school graduates with low ability and previous work experience were assumed to have identical reservation wages, for instance. This is consistent with our structural model, under which agents facing identical structural parameters must have identical reservation wages.[27] However, our data includes survey reports of each individual's reservation wage, which in general do not coincide with the reservation wages used in estimation. One way to reconcile these individual reserva-

[26] Appendix C describes details of these tests.

[27] If we used individual reservation wage reports directly in the estimation, we would essentially be estimating the parameters of *individual-specific* accepted wage and unemployment duration distributions using just one observation for each, which is intractable.

tion wages with the underlying structural model is to assume that one or more structural parameters faced by the individual, but not included in the likelihood function used for estimation, generated the reported reservation wage. In our model, the agent's flow value of leisure or net search cost (b), discount factor (δ), and probability of job separation (p) determine behavior but do not explicitly enter estimation. We use individual reservation wage reports to shed light on one of these parameters, the net search cost (b).[28] The results allow us to learn about individual heterogeneity in our sample in ways that are (arguably) richer than the standard approach of estimating a mixture distribution (Heckman and Singer, 1984), which requires a finite number of types (typically two or three) for tractable estimation.[29]

We estimate b as follows: for each individual, we use our maximum likelihood estimates of (λ, q); calibrate p according to observed job separations in the data (a monthly rate of approximately .04); choose $\delta = .95$ annually; and then choose $\hat{b}$ to match w^* to the individual's reservation wage report (through a unidimensional method of moments estimation). This generates the distribution of $\hat{b}$ in our sample in a way that makes use of numerous sources of information, including the restrictions of our structural model, the distributions of accepted wages and unemployment durations on which our maximum likelihood estimates are based, and the individual heterogeneity incorporated in each agent's reported reservation wage. To our knowledge, this is the first use of reservation wage data to shed light on individual-specific search costs in this manner in the literature.[30]

[28] We choose b rather than δ or p because we think it the most likely source of individual-specific heterogeneity: reasonable priors allow us to calibrate δ, and p may be calibrated to match data on job separations within our sample.

[29] Note that our approach is possible due only to the availability of reservation wage reports; structurally estimated search models lacking such data would still have to use the Heckman and Singer approach, or some variant, to incorporate unobserved heterogeneity.

[30] Eckstein and Wolpin (1995) conduct a conceptually similar exercise, using their structural model to recover search costs after estimating the remaining parameters. However, since they lack individual data on reservation wages, they are limited to using their reservation wage estimates defined within the cells of their model.

We find the distribution of $\hat{b}$ under each variation of reservation wages used in estimation of the model (w^*, w_{q_5} and w^*_{MLE}). We then use these estimates of individual-specific search costs to test the predictions of our model. Specifically, our model predicts that those with lower net search costs (i.e., higher b) will have higher reservation wages, and therefore experience longer unemployment durations and receive higher accepted wages, all else equal. We can test these predictions by regressing these labor market outcomes on our estimates of search costs, while also controlling for the covariates included in our structural estimation. If our estimates of search costs accurately capture aspects of individual heterogeneity relevant to search behavior, then we should see a positive correlation between unemployment durations, the probability of a censored unemployment spell (i.e., the probability of failing to obtain a job by the end of the sample), accepted wages and search costs.

This is (partially) confirmed in Table 12, which presents results of regressions of unemployment durations, the censoring indicator and accepted wages on $\hat{b}$, our search cost estimate for each individual (standard errors are bootstrapped to account for sampling variation in $\hat{b}$). We find that the coefficient on $\hat{b}$ is positive in all regressions, as predicted, regardless of the variant of the reservation wage used in the underlying structural estimation (although statistically significant coefficients are obtained only for accepted wages). The results are not very large in magnitude, however: for example, for accepted wages (columns (7)-(9)), an increase of 100 rand in the value of leisure implies just a 5 rand increase in accepted wages. This suggests that search costs play a relatively unimportant role in labor market outcomes in our sample when compared with job arrival rates and wage offers. Nonetheless, our procedure to recover individual-specific search costs coincides with our theoretical model, and illustrates the value of using survey data on reservation wages to reveal information on heterogeneity in search behavior that would otherwise remain unobserved.[31]

6 Policy Simulation: Employer Wage Subsidy

Because the parameters of the structural model represent the primitives of the search model and are therefore invariant to policy, our model may be used to simulate counterfactual outcomes of various policies. One such policy to consider is an employer wage subsidy, which we may model as an exogenous increase in the mean wage offer. Therefore, a subsidy s to hiring unemployed youth would truncate the wage offer distribution from below at s, leaving all other structural parameters unchanged.[32] One may think of the subsidy as a voucher, with nominal value s, that employers may apply towards a youth's wage. We may then calculate how various features of the model, such as the quantiles of the accepted wage and unemployment duration distributions and the proportion of offers accepted, change from the baseline case to that under the subsidy.

One complication that arises, however, in such simulation is calculation of w^*. Under the search model, a change in the wage offer mean (or any structural parameter) will change w^*, and hence the simulation results will depend crucially on how the model accounts for the agent's updated w^* in response to the policy change. When w^* is estimated structurally, the approach is straightforward: merely update the structural estimate of w^* under the new wage offer distribution. However, when w^* is estimated from the data, we must update

[31] Note that such an exercise would not be possible using the Heckman-Singer approach to unobserved heterogeneity, which recovers type-specific structural parameters and type proportions, but can map heterogeneity in parameters to particular observations only in a probabilistic sense. Our procedure, by contrast, uses survey data on reservation wages to map heterogeneity in search costs to individuals in the sample, and thus allow for more severe tests of our model predictions.

[32] Note that in our partial equilibrium framework, we do not model any effect the wage subsidy may have on the frequency of offers or on the destruction of jobs. Moreover, by assuming that the wage offer distribution becomes truncated below by s, we implicitly assume that the subsidy is fully passed through to job seekers in the form of wage offers, which would generally not be the case if employers have market power in the youth labor market. In this sense, our simulation results present a best-case scenario of the effect of the subsidy on employee welfare.

w^* by calibrating some elements of θ that we did not observe nor estimate in our baseline specification. In our simulation, we update w^* in the same fashion as in estimation of the search cost distribution described in the previous section. That is, we calibrate the model parameters not estimated by our model (b,δ,p) such that they reproduce the value of w^* used in the baseline estimation. As in the previous section in which we estimated search costs, we use our maximum likelihood estimates of (λ, q); calibrate p according to observed job separations in the data; choose $\delta = .95$ annually;and then choose b to match w^* to the data (through a unidimensional method of moments estimation, as described in the previous section). We then update w^* by varying the subsidy value s, holding all other parameters fixed.

Figures 5 and 6 show reservation wages and (mean) accepted wages, respectively, under a range of employer wage subsidy values.[33] The subsidy $s = 0$ corresponds to the baseline estimates discussed in the preceding sections, and s increases to 1,000 rand in increments of 100 along the horizontal axis. The figures show that both reservation wages and mean accepted wages increase (approximately) linearly in the amount of the subsidy, by about 60 rand per 100 rand increment in s,[34] showing that the benefits (in terms of increased mean accepted wages) of the subsidy recover only about 60% of its costs.[35] Reservation wages are uniformly greatest in the model with w^*, while reservation wages in the model with w^*_{MLE} are the next greatest. Results for mean accepted wages as a function of the subsidy (Figure 6) show a similar linear increase across all models.

The greater selectivity of youths in the model with w^* is also shown in Figure 7, which plots the probability of wage offer acceptance (i.e., $\Pr(w \geq w^*)$) for each model. The

[33]In Figures 5-9, the lines labeled `wrhat=wr` correspond to the model estimated with w^*; `wrhat=wp5` to w_{q_5}; and `wrhat=wrmle` to w^*_{MLE}.

[34]This equality is a consequence of the assumption of exponential wage offers, because the corresponding accepted wage distribution is shifted to the right by exactly the reservation wage.

[35]This ignores any benefits of the subsidy on reduced employment durations, which are considered later in this section.

probability of wage offer acceptance is nearly one half as low under w^* than under w_{q_5} for all subsidy values considered. Moreover, as the subsidy grows from 0 to 1,000 rand, the acceptance probability under w^* increases by only about 15 percentage points, while in the other models it grows by 20 percentage points or more.

Finally, Figures 8 and 9 plot the unemployment survivor function, or the probability that a youth experiences an unemployment spell of a given duration, for spells of 12 and 24 months, respectively. The figures show that the probability of such a lengthy unemployment spell is lowest in the model with w^* for all subsidy values, due to the higher offer arrival rates under that model. Moreover, the subsidy causes the likelihood of lengthy unemployment spells to fall the most in the model with w^* compared to the other models. Overall, the subsidy appears quite effective at reducing lengthy unemployment spells; the probability of experiencing an unemployment spell of at least 12 months decreases by a high of 15 percentage points in the model with w^*, and a low of 10 percentage points under w_{q_5}, as the subsidy increases from 0 to 1000 rand. Whether such a reduction produces 1,000 rand in social benefits (or at least enough social benefit when paired with increased accepted wages to exceed costs) is unclear and requires more formal analysis, however.

Our simulation of an employer wage subsidy shows that youths respond to the increased opportunities resulting from the subsidy by raising their reservation wages. However, the reservation wage increases are modest enough for the subsidy to have beneficial effects on accepted wages and unemployment durations. It is unclear, however, whether these benefits exceeds the subsidy's costs.

7 Conclusion

In this paper, we have presented a simple, standard search model in an effort to understand the role of reservation wages in explaining high observed unemployment rates and durations among Cape Town youth. Using data on accepted wages and unemployment durations for school leavers who found their first job, we estimated the parameters of a structural search model that incorporates observed heterogeneity and measurement error in wages. We estimated the model using survey reports of the reservation wage, as well as alternate measures including the 5th percentile of accepted wage offers and maximum likelihood estimation, for comparative purposes. Results using survey data on reservation wages suggested that searchers received job offers frequently, but at wages that were typically unacceptably low. In contrast, results using the 5th percentile of observed accepted wage offers and maximum likelihood estimation suggested less frequent offers, but a higher probability of offer acceptance. Accounting for observed heterogeneity revealed that, as expected, the frequency and quality of labor market opportunities are generally worse for disadvantaged groups, such as blacks, coloureds and the less skilled.

We used the results of the model, in combination with individual reservation wage reports, to estimate the full distribution of search costs in the sample. Correlations between our estimates of individual-specific search costs and labor market outcomes confirmed our model's predictions, at least with respect to accepted wages. Thus our model allows for insights into individual-specific heterogeneity relevant to search behavior that may not be inferred from the data alone, nor may it be captured in the standard approach of estimating a mixture distribution over unobserved types.

Finally, in a policy simulation of the effect of an employer wage subsidy, we found that although the subsidy has the unsurprising effect of increasing reservation wages, it nonetheless may have substantial positive benefits on accepted wages and unemployment durations. However, because we have assumed that firms will pass the subsidy along in full to employees, such positive effects may be considered an upper bound. A more complete model of firm response to the wage subsidy may find less beneficial effects for youth job seekers.

Returning to our initial motivating inquiry on the role of reservation wages in Cape Town youth unemployment, we found that implied wage offer acceptance rates are indeed substantially lower under the survey reports of the reservation wage than alternative measures. However, to reconcile these low acceptance probabilities with the observed data, the model estimates a correspondingly lower average wage offer. Moreover, if youths behave according to our model and their stated reservation wages, offers appear to arrive with much greater frequency than under alternative measures. The true role of reservation wages therefore depends on which picture of the Cape Town youth labor market–frequent but low offers, versus infrequent but high offers–is more accurate. While the latter picture is consistent with popular perception and is the one that would emerge from the data in the absence of reservation wage reports, the availability of reservation wage data allows us to suggest an alternative view of the youth labor market that is equally consistent with search theory. Although the high frequency of (relatively low) wage offers implied by our estimates may not literally be occurring in the South African youth labor market, our results are consistent with a labor market that is inefficient at matching employers to employees, leading to a high "implicit refusal" rate.

Given the simplicity of our model in its current form, there is much scope for further work. For instance, our model conditions on youths' exit from school, when in fact this decision may also be viewed in light of dynamic optimization. Future work will endogenize the decision to exit school and enter the labor market that we model in this paper.

References

Banerjee, Abhijit, Sebastian Galiani, James Levinsohn, Zoë McLaren and Ingrid Woolard. "Why Has Unemployment Risen in the New South Africa?" NBER Working Paper Series No. 13167, June 2007.

Bound, John and Alan B. Krueger. "The Extent of Measurement Error in Longitudinal Earnings Data: Do Two Wrongs Make a Right?" *Journal of Labor Economics*, Vol. 9, No. 1 (Jan., 1991), pp. 1-24.

Cameron, A. Colin and Pravin K. Trivedi. *Microeconometrics: Methods and Applications.* New York: Cambridge University Press, 2005.

Case, Anne. "Does Money Protect Health Status? Evidence from South African Pensions." Mimeo, Princeton University 2001.

Christensen, Bent Jesper and Nicholas M. Kiefer. "The Exact Likelihood Function for an Empirical Job Search Model." *Econometric Theory* 7, 1991: 464-486.

Christensen, Bent Jesper and Nicholas M. Kiefer. "Measurement Error in the Prototypal Job-Search Model." *Journal of Labor Economics*, Vol. 12, No. 4. (Oct., 1994), pp. 618-639.

Dinkelman, Taryn and Vimal Ranchhod. "Evidence on the impact of minimum wage laws in an informal sector: Domestic workers in South Africa." Mimeo, 2010.

Eckstein, Zvi and Gerard J. van den Berg. "Empirical labor search: a survey." *Journal of Econometrics* 136, 1987: 531-564.

Eckstein, Zvi and Kenneth I. Wolpin. "Duration to First Job and the Return to Schooling: Estimates from a Search-Matching Model." *Review of Economic Studies* 62, 1995: 263-286.

Flinn, C. and J. Heckman. "New Methods for Analyzing Structural Models of Labor Force Dynamics." *Journal of Econometrics* 18, 1982: 115-168.

Heckman, J. and B. Singer. "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data." *Econometrica* Vol. 52(2), 1984.

Hertz, Tom. "The Effect of Minimum Wages on the Employment and Earnings of South Africas Domestic Service Workers." Mimeo, 2005.

Lancaster, Tony and Andrew Chesher. "An Econometric Analysis of Reservation Wages." *Econometrica* 51(6), November 1983: 1661-1676.

Leibbrandt, Murray, James Levinsohn and Justin McCrary. "Incomes in South Africa since the fall of Apartheid." Mimeo, 2005.

Lynch, Lisa M. "Job Search and Youth Unemployment." *Oxford Economic Papers* New Series, Vol. 35, Supplement: The Causes of Unemployment (Nov., 1983), pp. 271-282.

Nattrass, Nicoli and Richard Walker. "Unemployment and Reservation Wages in Working-Class Cape Town." *South African Journal of Economics* 73(3), September 2005.

Nickell, Stephen. "Biases in Dynamic Panels with Fixed Effects." *Econometrica*, Vol. 49, No. 6 (Nov., 1981), pp. 1417-1426.

Schöer, Volker and Murray Leibbrandt. "Determinants of Job Search Strategies: Evidence from the Khayelitsha/Mitchell's Plain Survey." *South African Journal of Economics* 74(4), December 2006.

Van den Berg, Gerard J. "Nonstationarity in Job Search Theory." *Review of Economic Studies* 57, 1990: 255-277.

Van den Berg, Gerard J. and Geert Ridder. "An Empirical Equilibrium Search Model of the Labor Market." *Econometrica* Vol. 66, No. 5. (Sep., 1998), pp. 1183-1221.

White, Halbert. "Maximum Likelihood Estimation of Misspecified Models." *Econometrica* Volume 50, No. 1 (January 1982).

Wolpin, Kenneth I. "Estimating a Structural Search Model: The Transition from School to Work." *Econometrica* 55(4), July 1987: 801-817.

Yamada, Hiroyuki. "The Impact of the Introduction of Sectoral Minimum Wages on Low Wage Markets in a Low Income Country: Evidence from South Africa." Mimeo, 2007.

A Derivation of Likelihood Function

This appendix provides more detail on the derivation and form of the likelihood function used in model estimation. The likelihood function is composed of two additively separable parts that follow from the search model: the accepted wage distribution and the unemployment duration distribution. We consider each in turn:

Accepted wage distribution

Under our assumption that wage offers are distributed exponential(λ), the accepted wage distribution is:

$$
\begin{aligned}
f_W(w|w \geq w^*) &= \frac{f_W(w)}{1 - F_W(w^*)} \\
&= \frac{1}{\lambda} \exp\left(-\frac{w - w^*}{\lambda}\right)
\end{aligned}
$$

Because we also assume that wages are measured with error such that $w_o = w + \epsilon$, where w_o is the observed accepted wage and ϵ is distributed $N(0, \sigma_\epsilon^2)$, we have the following distribution of observed accepted wages:

$$
\begin{aligned}
f_W(w_o|w \geq w^*) &= \int_{-\infty}^{\bar{\epsilon}} f_W(w_o|w \geq w^*, \epsilon)\phi\left(\frac{\epsilon}{\sigma_\epsilon}\right) d\epsilon \\
&= \int_{-\infty}^{\bar{\epsilon}} \frac{1}{\lambda} \exp\left(-\frac{w_o - \epsilon - w^*}{\lambda}\right) \phi\left(\frac{\epsilon}{\sigma_\epsilon}\right) d\epsilon \\
&= \exp\left(\frac{-2w_o\lambda + 2w^*\lambda + \sigma_\epsilon^2}{2\lambda^2}\right) \times \frac{1}{\lambda}\phi\left(\frac{w_o - w^*\lambda + \sigma_\epsilon^2}{\lambda\sigma_\epsilon}\right)
\end{aligned}
$$

where $\phi(\cdot)$ is the standard normal distribution, and $\bar{\epsilon} = w_o - w^*$ is the upper bound on the distribution of ϵ.

Unemployment duration distribution

Under our assumption of Poisson offer arrivals, the hazard of unemployment exit h is the (constant) product of the offer arrival rate q and the probability that the offer will be accepted, i.e., $h = q(1 - F_W(w^*))$. Accordingly, unemployment durations d are distributed exponentially with parameter h, so that $f_D(d) = h\exp(-hd)$. Because some unemployment spells are right-censored, the observed duration $d = \min\{d^*, d_c\}$, where d^* is the true duration and d_c is the duration observed when the spell was censored. Let $c = \mathbb{I}\{d = d_c\}$ be an indicator for censored spells. Then the density of observed unemployment durations, $g_D(d)$, is:

$$\begin{aligned} g_D(d) &= f_D(d)^{1-c}[1 - F_D(d)]^c \\ &= [h\exp(-hd)]^{1-c}[\exp(-hd)]^c \end{aligned}$$

Finally, let $m = \{0, 1\}$ be an indicator for missing wage data (either due to a censored unemployment spell or otherwise). The individual's likelihood contribution is the (log) sum of the observed accepted wage and unemployment duration densities:

$$L(\theta) = (1 - m)\ln f_W(w_o|w \geq w^*; \theta) + \ln g_D(d; \theta)$$

for $\theta = (q, \lambda, \sigma_\epsilon)$.

B Data

The sample is all young adults in CAPS who have exited school, are observed for at least 12 months since leaving school in the calendar data, and have non-missing reservation wage data (reservation wage measure defined below). Additionally, those below the 1st and above the 99th percentiles of accepted wages are dropped. School exit is defined as at least 3 consecutive months of school absence in the calendar data (only 6% report returning to school after a minimum 3-month absence, none of them full-time). Time is calculated relative to month of school exit, so that month 1 is the first of the minimum 3 consecutive months of school absence that define school exit.

Unemployment duration is calculated relative to month of school exit, so that minimum unemployment duration is one month. An unemployment spell ends when the youth reports working in any job in a calendar month, where work is defined as employment for pay, in-kind benefits or "family gain." Censored observations are those that had not completed their first unemployment spell by the end of the observation period (December 2006).

The observed wage is the first reported wage after school exit across Waves 1-4, adjusted for monthly CPI (base is August 2002, the first month of calendar data) at the time of interview and scaled to full-time monthly equivalent based on 160 working hours per month (those reporting monthly hours above 160 are considered full-time and do not receive an adjustment). Wages reported in Waves 2-4 are the sum of wages reported across all jobs held.

When the reservation wage is based on survey data, it is the value from the most recent interview before conclusion of the first unemployment spell since exiting school. For Wave 1, the reservation wage $w^* = w^*_{moft}$, where w^*_{moft} is the response to the question, "What is the lowest monthly wage you would accept for full-time work?" For Waves 2-4, the reservation wage is defined as $w^* = \min\{w^*_{moft}, w^*_{revealed}\}$, where $w^*_{revealed}$ is the lowest wage associated with an affirmative response to the series of questions, "Would you accept a job doing occupation x at monthly wage w?" Reservation wages are adjusted for monthly CPI (August 2002 base) at the time of interview. For those with a censored first unemployment spell, the reservation wage is the last reported reservation wage in the panel.

Search is defined as a positive response to the "Searched for work in this month?" question in the calendar data. The job separation probability is calibrated as total number of separations from the first job divided by total months employed in first job since leaving school for all observations in the sample.

Age is age in years at school exit. Schooling is years of completed schooling at school exit. The ability proxy is the z-score from the literacy and numeracy evaluation (LNE) administered by CAPS in Wave 1. The "previously worked" variable is an indicator for whether the youth worked for pay (i.e., reported a non-zero wage) in the panel prior to school exit. Full-time work is defined as an an average of at least 35 hours per month. The unemployment rate in the youth's subplace is from the 2001 Census. A subplace is described as “a local social boundary equivalent to a split suburb or merged suburb in urban formal areas, a locality in the informal areas and a village in the traditional areas.”[36] Cape Town has 683 subplaces.

The survey weight is the young adult sample weight, which is adjusted for the sample design plus household and young adult non-response.

[36] Dube, “Census Geography of South Africa,” http://www.statssa.gov.za/africagis2005/presentations/oralcolemandube.pdf

C Tests of Model Fit

This appendix discusses the formal test of model fit we use to compare our predicted unemployment duration and accepted wage distributions to the data. For continuous data, Cameron and Trivedi (2005, pp. 261-2) propose a variation of the Lagrange Multiplier (LM) test using the sample moments and scores from the estimated model.[37] Let $\hat{m}_i = m(x_i, \hat{\theta})$ be the sample moment(s) for observation i evaluated at the estimated parameters $\hat{\theta}$. For instance, for exponential wage offers we would have $\hat{m}_i = w_i - (\hat{\lambda} + w^*)$. Let $\hat{s}_i = s(x_i, \hat{\theta}) = \frac{\partial \ln L_i}{\partial \hat{\theta}}$ be the score vector for observation i evaluated at $\hat{\theta}$. Under the null hypothesis that the model is correctly specified, $E(m) = E(s) = 0$. Cameron and Trivedi propose the following auxiliary regressions:

$$
\begin{aligned}
1 &= \hat{m}_i' \delta + \hat{s}_i' \gamma + u_i \\
1 &= \hat{m}_i' \delta + u_i
\end{aligned}
$$

where 1 is a vector of ones and the second auxiliary regression is valid in the case where $\frac{\partial m}{\partial \theta} = 0$, as it is in our case. The corresponding test statistic is then:

$$M = NR_u^2$$

where R_u^2 is the uncentered R^2 from the auxiliary regression. Under the null, M is distributed $\chi^2(h)$, where h is the dimension of m (i.e., h is the number of moments).[38]

[37] Although many researchers use the Pearson χ^2 test to evaluate the fit of structural models, Cameron and Trivedi (2005, pp. 266) note that the test is invalid if the data are not generated from a multinomial distribution. Since our outcomes of interest (duration and wages) are continuous, we use the LM test described above.

[38] Another test of model fit that could be applied in our context is the Kolmogorov-Smirnov test, which is a nonparametric test for the equality of two distributions. However, when the parameters of one distribution are estimated using data from the other, the test statistic may not be asymptotically distributed according to the Kolmogorov distribution, invalidating the test.

Table 1: Summary statistics

Variable	N	Mean	Std. Dev.	Min	Max
female	1430	0.53	0.50	0	1
black	1430	0.26	0.44	0	1
coloured	1430	0.62	0.49	0	1
white	1430	0.12	0.32	0	1
age	1430	19.5	2.1	14	26
schooling	1430	10.7	2.1	0	16
ability score	1430	0.18	0.91	-2.97	2.01
wage	977	2486.4	1859.9	346.6	11642.3
reservation wage	1430	1594.2	1801.8	48.7	36645.8
$\mathbb{I}(w^* > w)$	977	0.24	0.43	0	1
first UE spell	1430	11.7	11.2	1	50
UE spell$\geq$1yr	1430	0.42	0.49	0	1
censor	1430	0.24	0.43	0	1
previously worked	1430	0.34	0.48	0	1
full-time	1027	0.77	0.42	0	1
subplace UE	1430	0.15	0.11	0	0.54
search intensity	1430	0.19	0.30	0	1
never searched	1430	0.35	0.48	0	1
return to school (ft)	1430	0.00	0.00	0	0
return to school	1430	0.06	0.23	0	1

Sample is youths who have left school (absent at least 3 consecutive months after attending school at least one month in calendar sample), observed for at least 12 months in calendar sample after school exit, and with valid reservation wage data. Age and schooling measured at time of school exit. Ability score is z-score from literacy and numeracy evaluation administered in Wave 1. Wage is first reported wage following completion of first unemployment spell. Reservation wage is last reported reservation wage before first completed unemployment spell or censoring. Observations below 1st percentile and above 99th percentile of accepted wages dropped. Wages and reservation wages in real rand per month, base month August 2002 (South African rand/US dollar exchange rate at base=10.59). $\mathbb{I}(wr > w)$ is indicator that reservation wage exceeds reported accepted wage. Previously worked refers to work experience in calendar history prior to school exit. Full-time is average of at least 35 hours per week of work in last month. Subplace UE is unemployment rate in subplace, 2001 Census. Subplace UE is unemployment rate in subplace, 2001 Census. Search intensity is fraction of months spent searching before completion of first unemployment spell or censoring. Never searched excludes those who obtain employment immediately after school exit. Statistics calculated using sample weights ($weightyr$).

Table 2: Unemployment, by observable characteristics

	First UE spell	UE spell≥1yr	UE spell≥2yrs	UE, month 12	censored
male	10.2	0.35	0.23	0.47	0.19
female	13.0	0.49	0.34	0.56	0.28
African	17.2	0.66	0.52	0.72	0.38
coloured	10.2	0.36	0.20	0.48	0.20
white	7.7	0.21	0.24	0.28	0.14
age:					
≤18	13.9	0.50	0.35	0.59	0.33
19-22	10.9	0.39	0.25	0.50	0.20
≥23	7.4	0.27	0.18	0.34	0.11
schooling:					
≤9	16.3	0.59	0.43	0.70	0.38
10 or 11	12.7	0.48	0.28	0.55	0.28
12	9.2	0.32	0.19	0.42	0.15
>12	5.0	0.15	0.15	0.29	0.07
low ability	14.3	0.54	0.37	0.63	0.31
high ability	8.7	0.29	0.19	0.39	0.16
previously worked	15.1	0.57	0.41	0.66	0.37
never worked before	5.2	0.14	0.05	0.25	0.00
some search	10.2	0.36	0.26	0.47	0.18
never searched	14.5	0.55	0.33	0.61	0.36

Age and schooling measured at time of school exit. “Low” and “high” ability refer to below and above within-sample median literacy and numeracy evaluation score. “Some search” is reported search in at least one month prior to completion of first UE spell or censoring. “Previously worked” means work experience reported in calendar history prior to school exit. Never searched excludes those who obtain employment immediately after school exit. First unemployment spell measured in months; all other statistics are means of indicator variables. “UE, month 12” refers to employment at month 12 following school exit. All statistics weighted by sample weights.

Table 3: How obtained first job since school exit

	Full sample	Black	Coloured	White
informal network (household)	13.6	12.1	15.2	7.4
informal network (non-household)	46.5	49.6	47.2	36.3
formal	30.7	32.0	28.8	39.2
past work for firm	1.7	1.0	2.2	0.0
self-employed/family	3.9	3.3	3.8	5.4
other/don’t know	3.6	2.1	2.7	11.7

Table shows method of obtaining first job, proportion by race. Sample weights used in calculation.

Table 4: Post-school activities

Variable	N	**Mean**	**Std. Dev.**
Wave 4 (2006)			
dead	1430	0.00	0.03
moved	1430	0.04	0.19
attrited	1430	0.12	0.32
married	1278	0.06	0.23
pregnant (inc. males)	1278	0.04	0.19
own child in HH	1278	0.18	0.39
live with at least one parent	1278	0.78	0.41
pension recipient in HH	1278	0.17	0.38
Wave 3 (2005)			
seriously ill	1170	0.07	0.26
unpaid work	1170	0.09	0.29

Variables for each wave calculated only for those who had left school by time of interview. "Pregnant" includes males who report their partners as pregnant. "Seriously ill" refers to self-reported inability to perform normal activities. All statistics calculated using sample weights.

Table 5: Reservation wage regressions

	(1)	(2)
Dependent variable	w_i^*	w_i^*
female	-89.8	-102.9
	(107.2)	(114.9)
black	-754.3	-827.7
	(244.3)***	(233.8)***
coloured	-507.4	-449.6
	(241.3)**	(247.5)*
age	-109.6	-63.5
	(183.9)	(176.1)
age^2	3.9	3.2
	(4.7)	(4.5)
schooling	90.3	93.8
	(31.9)***	(31.0)***
ability score	281.9	303.8
	(74.4)***	(75.9)***
pensioner in HH		-181.1
		(106.0)*
father employed		69.1
		(128.5)
ill		117.4
		(190.1)
parents want youth to work		-79.9
		(25.4)***
co-resident with parent		180.8
		(79.0)**
own child in HH		-274.1
		(138.5)**
N	1430	1430
R^2	0.09	0.13

Robust standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. Reservation wage w_i^* is individual-specific survey report, as defined in Appendix B. Age and schooling measured at time of school exit. Pensioner in HH, father employed, ill, parents want to work, co-resident with parent, and own child in hh variables measured at time of reservation wage, where reservation wage is last report prior to job acceptance or end of calendar sample. "Ill" refers to self-reported illness that prevents normal activities. "Parents want youth to work" measured on self-reported 1-5 scale, with 5 being strongest. All regressions include fixed effects for wave at which w^* measured.

Table 6: Regressions of w^* and w_{q_5} on covariates used in model estimation

	(1)	(2)
Dependent variable	w^*	w_{q_5}
constant	1575.1	1279.0
	(33.0)***	(122.8)***
black	-797.4	-814.5
	(33.9)***	(126.0)***
coloured	-592.5	-700.2
	(31.4)***	(104.6)***
HS grad	318.1	251.9
	(10.2)***	(35.9)***
at least some college	628.8	615.2
	(31.1)***	(59.1)***
high ability	264.7	78.8
	(10.5)***	(50.1)
previously worked	-119.6	51.7
	(14.0)***	(39.1)
N	1430	1423
R^2	0.88	0.57

Robust standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. w^* is median reservation wage by cell defined by included covariates. w_{q_5} is 5th percentile of accepted wages, by cell defined by covariates. "High ability" is indicator for above median literacy and numeracy evaluation score within sample. "Previously worked" means work experience reported in calendar history prior to school exit.

Table 7: Regressions of w^* on unemployment duration

	(1)	(2)
	w^*	w^*
unemployment duration	140.2	56.7
	(89.1)	(33.5)*
N	1126	1582
R^2	0.64	0.64
Individual fixed effects	x	x
Wave fixed effects	x	x
First UE spell only	x	
Spell fixed effects		x

Robust standard errors in parentheses, clustered by individual: * significant at 10%; ** significant at 5%; *** significant at 1%. Sample is person-years from estimation sample. Reservation wage measured in (real) rand per month; unemployment duration in months. All regressions use survey weights and include individual and wave fixed effects. Regressions including multiple spells include fixed effects for spell number.

Table 8: Parameter estimates, using reservation wage survey reports

Parameter	$\ln q$ **(offer arrival rate)**	$\ln \lambda$ **(wage offer parameter)**	$\ln \sigma_\epsilon$ **(measurement error s.d.)**
baseline level	0.27	710.58	495.11
constant	-1.30	6.57	6.20
	(0.29)	(0.17)	(0.05)
black	-0.80	-0.32	
	(0.32)	(0.19)	
coloured	-0.40	-0.13	
	(0.26)	(0.15)	
HS grad	0.48	0.27	
	(0.13)	(0.07)	
at least some college	0.69	0.54	
	(0.19)	(0.11)	
high ability	0.27	0.15	
	(0.12)	(0.07)	
previous work	0.37	0.73	
	(0.12)	(0.09)	
N	1430		
$\ln L$	-1,055,884		
$\Pr(w \geq w^*)$	0.29		
σ_ϵ (measurement error s.d.) as percentage of observed accepted wage s.d.	0.27		

Robust standard errors in parentheses. Estimation is by maximum likelihood, with reservation wage as median reservation wage from survey within covariate cell. Starting values taken from converged estimates of sequential estimation of wage offer and unemployment duration distributions. Optimization algorithm alternates between BFGS and BHHH. "Baseline level" refers to value of exponentiated constant term for each parameter, and may be interpreted as parameter level for left-out category (white high school dropouts of low ability, with no previous work experience). $\Pr(w \geq w^*)$ calculated as mean over distribution of full sample, i.e., $\Pr(w \geq w^*) = \int \Pr(w \geq w^*|x) f(x) dx$.

Table 9: Parameter estimates, using alternate reservation wage measures

	(1)	(2)	(3)
Reservation wage	w^*	w_{q5}	w^*_{MLE}
$\ln q$ **(offer arrival rate): baseline**	0.27	0.07	0.15
constant	-1.30	-2.64	-1.88
	(0.29)	(0.20)	(0.24)
black	-0.80	-0.51	-0.74
	(0.32)	(0.20)	(0.23)
coloured	-0.40	-0.12	-0.33
	(0.26)	(0.18)	(0.19)
HS grad	0.48	0.54	0.43
	(0.13)	(0.09)	(0.13)
at least some college	0.69	0.92	0.73
	(0.19)	(0.18)	(0.20)
high ability	0.27	0.25	0.10
	(0.12)	(0.10)	(0.13)
previous work	0.37	1.13	0.78
	(0.12)	(0.09)	(0.12)
$\ln\lambda$ **(wage offer parameter): baseline**	710.58	1445.88	899.51
constant	6.57	7.28	6.80
	(0.17)	(0.15)	(0.12)
black	-0.32	-0.53	-0.33
	(0.19)	(0.16)	(0.13)
coloured	-0.13	-0.34	-0.17
	(0.15)	(0.13)	(0.10)
HS grad	0.27	0.22	0.27
	(0.07)	(0.07)	(0.08)
at least some college	0.54	0.49	0.55
	(0.11)	(0.11)	(0.12)
high ability	0.15	0.11	0.20
	(0.07)	(0.07)	(0.09)
previous work	0.73	0.41	0.61
	(0.09)	(0.07)	(0.09)
$\ln\sigma_\epsilon$ **(measurement error s.d.): baseline**	495.11	262.09	322.73
constant	6.20	5.57	5.78
	(0.05)	(0.09)	(0.07)
$\ln w^*$**: baseline**			1304.30
constant			7.17
			(0.11)
black			-0.64
			(0.10)
coloured			-0.44
			(0.09)
HS grad			0.20
			(0.06)
college			0.40
			(0.10)
high ability			0.09
			(0.06)
previous work			-0.09
			(0.07)
N	1430	1430	1430
$\ln L$	-1,055,884	-1,055,534	-1,052,301
$\Pr(w \geq w^*)$	0.29	0.59	0.44
σ_ϵ (measurement error s.d.) as percentage of observed accepted wage s.d.	0.27	0.14	0.17

Robust standard errors in parentheses. Reservation wages at top row refer to inputs of maximum likelihood estimation: w^* is median reservation wage from data; w_{q5} is 5th percentile reservation wage; and w^*_{MLE} is maximum likelihood estimate (all by cell defined by included covariates). Estimation is by maximum likelihood, with starting values taken from converged estimates of sequential estimation of wage offer and unemployment duration distributions. Optimization algorithm alternates between BFGS and BHHH. "Baseline" refers to value of exponentiated constant term for each parameter, and may be interpreted as parameter level for left-out category (white high school dropouts of low ability, with no previous work experience). $\Pr(w \geq w^*)$ calculated as mean over distribution of full sample, i.e., $\Pr(w \geq w^*) = \int \Pr(w \geq w^*|x) f(x)dx$.

Table 10: Empirical and predicted unemployment survivor functions

	$\mathbf{Pr}(d \geq d_0)$			
	(1)	(2)	(3)	(4)
Reservation wage	**empirical**	w^*	w_{q_5}	w^*_{MLE}
UE duration (months)				
3	0.69	0.75	0.75	0.75
6	0.58	0.60	0.60	0.60
12	0.42	0.42	0.43	0.42
24	0.16	0.25	0.25	0.25
36	0.04	0.15	0.16	0.16
χ^2 (moments)		424.7	399.3	430.7
p-value		0.00	0.00	0.00
χ^2 (Pearson)		2821.1	2983.7	2859.3
p-value		0.00	0.00	0.00

Each cell reports value of survivor function at UE duration in left-hand column, i.e., each cell gives the proportion of the unemployment duration distribution that is at least as great as the value in the left-hand column. Column (1) is empirical survivor function observed in the sample, while columns (2)-(4) give predicted survival function for models using the indicator reservation wage inputs. χ^2 (moments) statistic is from auxiliary regression of ones on sample moments; statistic is NR^2 from this regression, and is distributed $\chi^2(m)$, where $m = 1$ is the number of moments; see Cameron and Trivedi (2005, pp. 261-2). χ^2 (Pearson) statistic is from Pearson χ^2 test of equality of sample and predicted proportions, calculated by dividing sample into 50 discrete groups by unemployment duration. Appendix C describes these tests in greater detail.

Table 11: Moments and quantiles of empirical and predicted accepted wage distributions

	Accepted wage			
	(1)	(2)	(3)	(4)
Reservation wage	**empirical**	w^*	w_{q_5}	w^*_{MLE}
mean	2486.4	2346.4	2336.0	2295.2
std. dev.	1859.9	1356.6	1682.5	1529.5
quantiles				
0.1	902.0	886.9	709.6	866.6
0.25	1299.9	1341.2	1087.4	1224.6
0.5	1835.2	1969.7	1760.6	1789.8
0.75	3108.0	2899.8	2915.4	2753.2
0.9	4961.0	4278.9	4676.0	4282.1
χ^2 (moments)		221.7	204.0	196.8
p-value		0.00	0.00	0.00
χ^2 (Pearson)		38.7	53.6	26.7
p-value		0.00	0.00	0.00

Each cell reports corresponding moment or quantile of observed accepted wages for empirical wage distribution (column 1) and predicted wage distribution by reservation wage input used in model estimation (columns 2-4). χ^2 (moments) statistic is from auxiliary regression of ones on sample moments; statistic is NR^2 from this regression, and is distributed $\chi^2(m)$, where $m = 1$ is the number of moments; see Cameron and Trivedi (2005, pp. 261-2). χ^2 (Pearson) statistic is from Pearson χ^2 test of equality of sample and predicted proportions, calculated by dividing sample into discrete groups by quantiles of accepted wages; 5th, 10th, 25th, 50th, 75th, 90th and 95th percentiles used. Appendix C describes these tests in greater detail.

Table 12: Regressions of labor market outcomes on estimated search costs

Panel A: Unemployment duration	(1)	(2)	(3)
$\hat{b}$	0.034	0.022	0.028
	(0.053)	(0.058)	(0.062)
N	1430	1430	1430
R^2	0.24	0.24	0.24
Panel B: Censored duration	(4)	(5)	(6)
$\hat{b}$	0.002	0.001	0.002
	(0.002)	(0.002)	(0.002)
N	1430	1430	1430
R^2	0.19	0.19	0.19
Panel C: Accepted wage	(7)	(8)	(9)
$\hat{b}$	0.049	0.048	0.051
	(0.016)***	(0.017)***	(0.018)***
N	977	977	977
R^2	0.29	0.28	0.28
w^* used	w^*	w_{q_5}	w^*_{MLE}

Robust standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions include covariates used in structural model estimation: dummies for black, coloured, HS grad, at least some college, high ability and previous work experience. $\hat{b}$ calculated by calibrating search cost so that w_i^* matches w^* from structural model, with discount factor $\delta = .95$ annually and separation probability p calibrated from observed separations from first job in sample. $\hat{b}$ measured in thousands for regressions with unemployment duration and censoring indicator as outcomes. All regressions use survey weights. Standard errors calculated by bootstrap (500 replications).

Figure 1: Youth employment/population in the US and South Africa

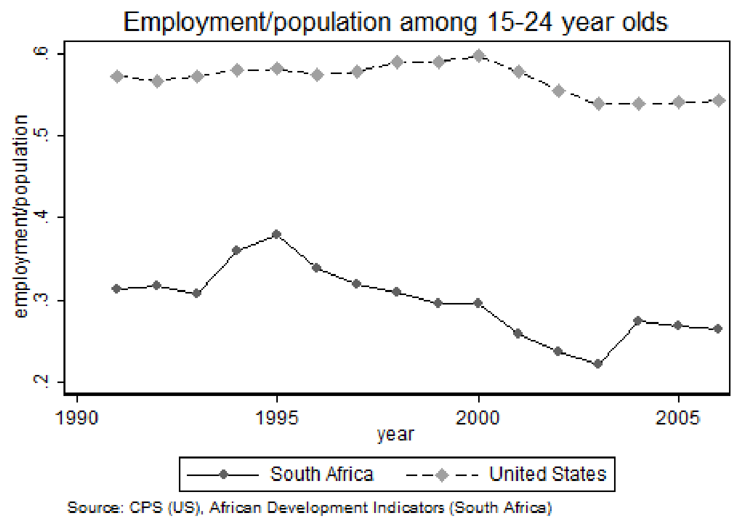

Figure 2: Wages and reservation wages

Full-time equivalent wages based on 160 hours of work per month.

Figure 3: Density of accepted wages

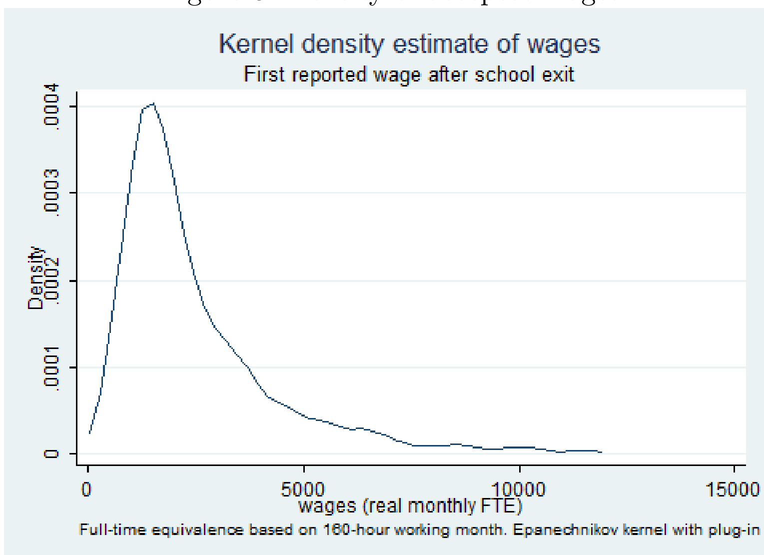

Figure 4: Density of first unemployment spell

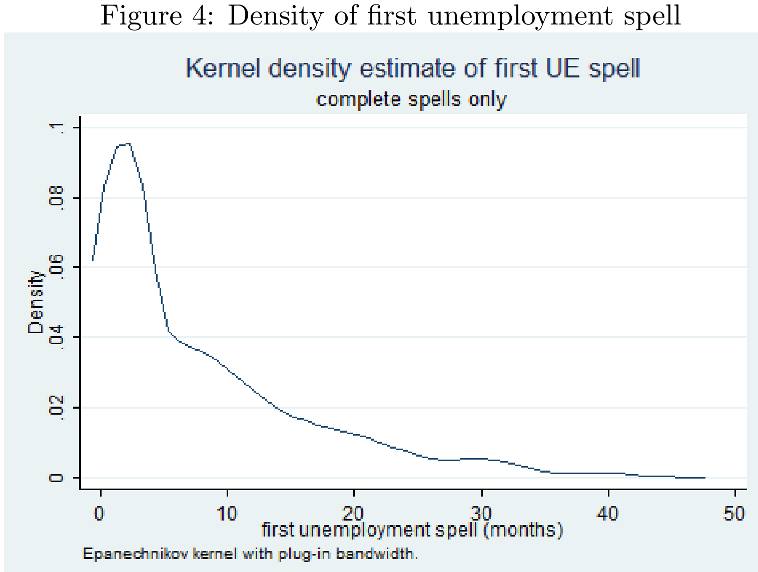

Figure 5: Reservation wages under employer wage subsidy

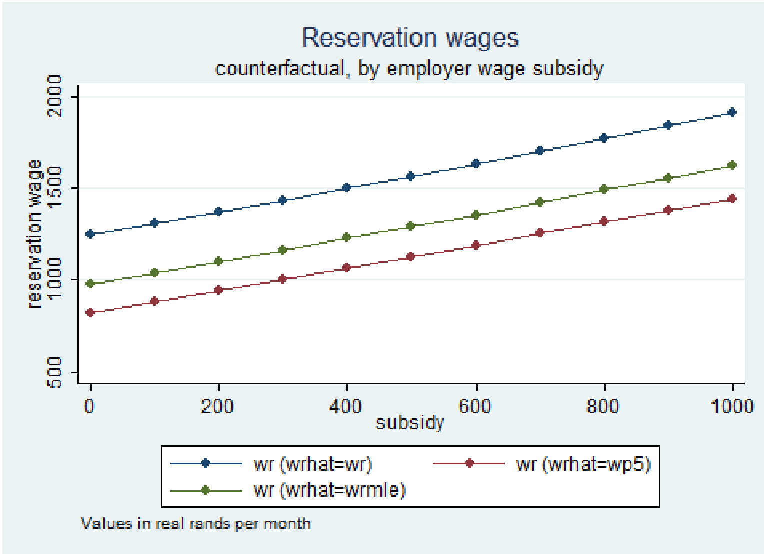

Figure 6: Accepted wages under employer wage subsidy

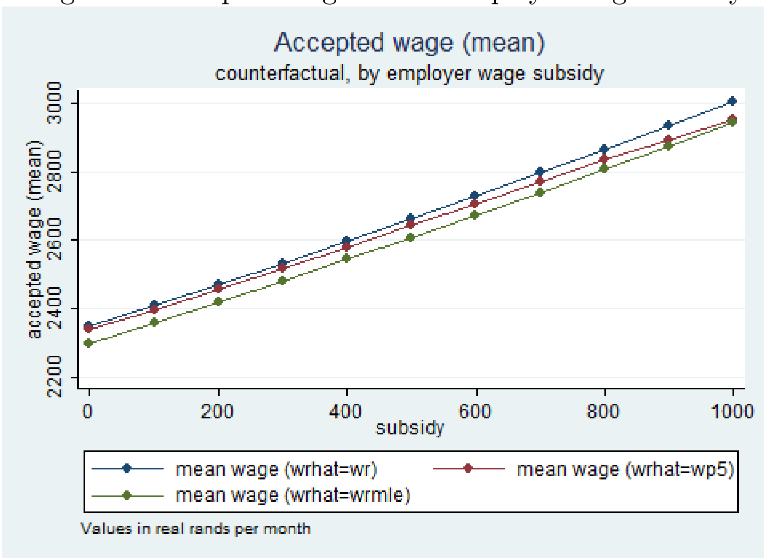

Figure 7: Probability of offer acceptance under employer wage subsidy

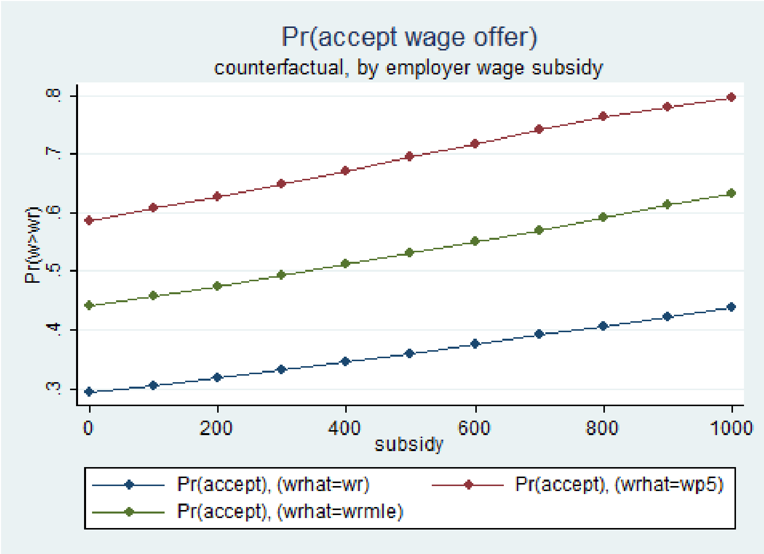

Figure 8: Unemployment survivor function under employer wage subsidy: 12-month UE spell

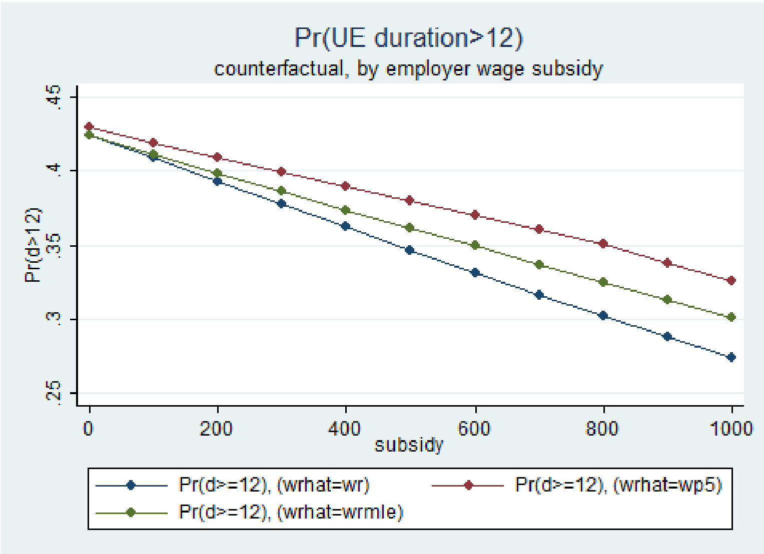

Figure 9: Unemployment survivor function under employer wage subsidy: 24-month UE spell