Prospective Analysis of a Wage Subsidy for Cape Town Youth

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Abstract

Persistently high youth unemployment is one of the most pressing problems in South Africa. We prospectively analyze an employer wage subsidy targeted at youth, a policy recently enacted by the South African government to address the issue. Recognizing that a credible estimate of the policy's impact requires a model of the labor market that itself generates high unemployment in equilibrium, we estimate a structural search model that incorporates both observed heterogeneity and measurement error in wages. Using the model to simulate the policy, we find that a R1,000/month wage subsidy paid to employers leads to an increase of R571 in mean accepted wages and a decrease of 12 percentage points in the share of youth experiencing long-term unemployment.

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1 Introduction

Unemployment among the young in South Africa is stunningly high and frustratingly persistent. Using the *narrow* ILO definition of unemployment which requires one to have actively sought work in the past four weeks, unemployment among 20-24 year olds exceeds 50 percent. These rates have persisted for over a decade.[1] In response, the South African government has enacted a employer wage subsidy to hire unemployed youth, which went into effect January 1, 2014. Understanding how the policy affects youth outcomes is crucially important, but an observational study will require additional time to gauge its effects. In this paper, we prospectively analyze such a policy for the Cape Town metro area.

Any analysis of a wage subsidy must be embedded in a model that generates equilibrium unemployment, given the magnitude and persistence of South African youth unemployment. Accordingly, we estimate a structural job search model in which reservation wages play a prominent role. In our model, an individual's reservation wage is an optimal response to labor market frictions that generate equilibrium unemployment. We then use our model to analyze the impact of a wage subsidy. Intuitively, the reservation wage is that which leaves an individual indifferent between accepting a job today and continuing to search. In this dynamic model, a wage subsidy increases both the value of search and the value of employment, resulting in a higher reservation wage. The impact of a wage subsidy in this context is nuanced.

The paper's contributions are two-fold. On the policy front, the paper analyzes the efficacy of a wage subsidy to Cape Town youth. We find that while a wage subsidy does lead youth to increase their reservation wages, they do so by a modest amount, such that the subsidy increases accepted wages and reduces the probability of lengthy unemployment spells. Specifically, we find that a R1,000/month wage subsidy paid to employers leads to an increase of R571 in mean accepted wages and a decrease of 12 percentage points in the share of youth experiencing long-term unemployment. On the methodological front, the paper is the first to apply data on reservation wages from a developing country to estimate a structural search model. Our model incorporates measurement

[1] See Banerjee, Galiani, Levinsohn, McLaren and Woolard (2008) for the exact figures and for a discussion of the causes behind the post-apartheid increase in unemployment.

error in reported wages and observed heterogeneity in the structural parameters.

The paper is also part of an extensive literature on unemployment in South Africa. For our purposes, the most relevant is the recent literature on search and reservation wages in Cape Town. Using the Cape Area Panel Study (CAPS), which we also use in this paper, Lam, Leibbrandt and Mlatsheni (2009) document the lengthy unemployment spells faced by Cape Town youth who exit school. 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. Using the same KMP data, Schoer and Leibbrandt (2006) find that several different search strategies prevail in the data. An employer-based wage subsidy for youth in South Africa is discussed in Pauw and Edwards (2006), Levinsohn (2008), Go, Kearney, Korman, Robinson and Thierfelder (2010), Burns, Edwards and Pauw (2010), and Burns, Edwards and Pauw (2012). Levinsohn, Rankin, Roberts and Schoer (2013) discusses evidence from a randomized control trial of a youth wage subsidy. We later discuss how our results compare to that study.

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 of the search model. Section 5 presents results of the policy simulation of an employer wage subsidy. Section 6 concludes.

2 Model, Estimation and Identification

2.1 Model and Estimation

To use the terminology of Eckstein and Van Den Berg (2007), our model is a standard "classical job search" model. 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 1983, Van Den Berg 1990) to use survey data on the reservation wage in a structurally estimated search model.

We consider the infinite-horizon, continuous-time dynamic programming problem of an unemployed worker searching for a job, 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 for the reservation wage w^*:

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

Given values of b, δ, p and the parameters characterizing F_W, one may solve for w^* through policy function iteration using the above.

Note that this formulation does not explicitly account for two institutional features of the broader South African labor market: minimum wages and union wage-setting. With respect to the

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

former, several studies have found low enforcement of minimum wages in South Africa (Hertz 2005, Yamada 2007, Dinkelman and Ranchhod 2010). With respect to the latter, in our sample only 2 percent of employed respondents report being union members (CAPS, Wave 2).[3] To the extent that both of these features impact the distribution of wage offers and the job arrival rate, they are implicit in (3).

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., $\Pr(w < w^*) = 0$.[4] Therefore we have:

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

The corresponding density of observed wages is:

[3] See Magruder (2012) for a discussion of the extended consequences of bargaining councils on wage setting.

[4] 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.

$$f_W(w_o|w \geq w^*) = \int_{-\infty}^{\bar{\epsilon}} f_W(w_o|w \geq w^*, \epsilon)\frac{1}{\sigma_\epsilon}\phi\left(\frac{\epsilon}{\sigma_\epsilon}\right)d\epsilon \tag{5}$$

where $\phi(\cdot)$ is the standard normal density.[5]

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:

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

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.[6] 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]

[5]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.

[6]In our data, 43 of 943 observations with a completed unemployment spell fail to report wages, or less than 5% of the sample.

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

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

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] Note that the parameters (b, δ, p) of the theoretical model are not identified by the likelihood function. We describe estimation of the reservation wage w^* in the following subsection.

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, 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 first estimate the model using survey data on the reservation wage, because this is the most novel feature of our data. Because the CAPS data has the rare advantage of self-reported reservation wages, using it in estimation allows us to incorporate heterogeneity that would otherwise be obscured using conventional techniques. 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

[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., $q = \exp(\phi' X)$.

must have an identical reservation wage. We later check the sensitivity of our results to using the individual reservation wage reports.

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 for a fixed sample size (Flinn and Heckman 1982, Eckstein and Van Den Berg 2007).[9]

The theoretical model also provides a means to identify the reservation wage in a manner that is fully structural. Actually doing so in practice, though, is typically problematic. This is because the reservation wage is a boundary value (since it is the truncation point of the accepted wage distribution) so it cannot be estimated by maximum likelihood.[10] 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

3.1 Description

We use data from the Cape Area Panel Study (CAPS), a longitudinal study of youth in metropolitan Cape Town, South Africa (Lam, Ardington, Branson, Case, Leibbrandt, Menendez, Seekings and Sparks 2008). CAPS sampled about 4,800 youth aged 14-22 in Wave 1 (August-December 2002). We use data from the first four waves, the last of which was conducted in 2006. For our purposes, the most relevant features of the data are its monthly histories (for a period of 52 months from

[9]Flinn and Heckman (1982) and Eckstein and Van Den Berg (2007) note that any fixed order statistic of the accepted wage distribution consistently estimates w^*.

[10]Identification in this case requires specifying b, δ, and p which are not identified by the likelihood function.

2002-2006) of education, search and employment activity, as well as its questions on reservation wages. We focus only on those black and coloured youth who have 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 influence of outliers in the estimation. This leaves $N = 1,321$ individuals in the sample. Key variables are described in Appendix B.

Table 1 summarizes our sample selection rules and the nature of attrition in the data. In Panel A, we document how we arrive at our final sample. The largest group of observations are dropped because those youth who were out of school in Wave 1 have left-censored unemployment spells, which is well known to pose severe problems in duration analysis. Students, i.e., those who do not exit school during the panel, and those who are out of school for less than one year make up other large groups. We will later explore the sensitivity of results to their inclusion. Panel B documents attrition. In our context, youth exit the sample because they complete their first unemployment spell since exiting school or because this spell is right-censored. We treat right-censored spells by altering the likelihood function as in (6), following standard practice in duration models. The bulk of right-censored spells occur because the individual remained unemployed during the last interview. Other reasons for right-censoring could be problematic if attrition is selective on characteristics related to employment and wage outcomes, but these comprise just 61 observations, or less than 5% of the sample.

Because our data contain only youth from metropolitan Cape Town, it is instructive to consider the representativeness of the sample in comparison to South African youth as a whole. Table A1 compares our sample to Census figures for youth from Cape Town and nationally. Coloured youth are the predominant group in Cape Town, and even more so in our sample than the Census, due to the earlier school exits of coloured students than their black counterparts. Capetonian youth are also relatively advantaged in relation to youth in other parts of the country, with higher average schooling, employment rates, and wages. These comparisons are useful to bear in mind when interpreting our results, and suggest that any labor market obstacles facing our sample are even

[11] We define school exit as being out of school for at least 3 consecutive months. A related paper, Pugatch (2012) uses this data to investigate school re-enrollment.

greater for South Africa more generally.

Table 2 presents summary statistics for the sample. Among the notable features are the high durations and rates of unemployment: mean duration to first job since school exit exceeds 12 months, while 45% of the sample is unemployed for at least one year. Observed search behavior appears low with 35% never searching since leaving school.[12] Nonetheless, few youth are returning to school: only 5% 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. Unlike many African economies, South Africa does not have a substantial informal sector. The mean accepted wage was 2,172 rand, with wages measured in real South African rand per month (base month August 2002, at which time the South African rand/US dollar exchange rate was 10.6). Table 2 appears quite consistent, at least on the surface, with a reservation wage story in which school leavers wait for a full-time, reasonably well-compensated job.

Table 3 presents unemployment durations and rates by observable characteristics. The data reveal expected patterns: unemployment is more prevalent and prolonged for 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: 22% 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 38% are censored, meaning that the remaining 62% 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 youth who may appear to be non-participants in the labor market may in fact be searching passively, or at least prepared to accept a job should an acceptable offer arrive.[13]

[12] We determine search behavior by responses to the survey question, "In which months (if any) were you looking for work?" The question was part of an exercise in which youth were asked to mark their activity (school, work, search, or none, in any combination) in all calendar months since their last interview. Any respondent reporting zero months of search activity since school exit is considered to have "never searched."

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

3.2 Self-reported reservation wages

Because reservation wages play a key role in our model, we further investigate 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).[14] Table 2 showed that 26% of those with completed spells and non-missing wage data report reservation wages that exceed their reported wage; Figure 1 is a graphical depiction of the same, with points below the 45-degree line indicating observations for which $w^* > w$. The model accounts for this phenomenon by estimating the distribution of measurement error in wages.

Another assumption of the model is that reservation wages are identical within all cells defined by covariates, as explained in Section 2.2. The presence of any unobserved heterogeneity affecting search behavior will make this assumption false, of course. We explore this possibility in Table A4, which presents statistics on the dispersion of self-reported reservation wages within covariate cell. Clearly, the data reject the assumption of homogeneous reservation wages among observationally identical individuals. A robustness check in which we replace the within-cell median reservation wage with individual reservation wages will later allow us to determine how much this heterogeneity alters our results.

Table 4 presents regressions of the reservation wage on a set of observable characteristics. Although not all coefficients are statistically significant, they generally enter with the expected sign: reservation wages are lower among females and blacks, who likely face more labor market disadvantages than similarly-skilled males and coloured youth; lower (convexly) as a function of age, suggesting that older youth are less patient in their search; higher for the more skilled, as proxied by schooling and ability; higher for those 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 who are ill or with their own children in the household, who have greater need to accept paid work. Notable exceptions to these sensible sign patterns are the negative coefficients on father's employment and pension receipt by a household member, which oppose the conven-

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

tional wisdom that availability of earned income and public benefits increase reservation wages, although the former coefficient is not statistically significant. The coefficient on co-residence with a pensioner would appear to contradict evidence that pension receipt makes younger household members healthier (Duflo 2003, Case 2004) and more likely to attend school (Edmonds 2006), both of which should increase reservation wages. However, other research has found that youth who are co-resident with pensioners exert less work effort, consistent with moral hazard (Souza 2010). Co-residence itself might be an endogenous response by younger household members with comparative advantage in skills suited to caring for aged family members, rather than for the labor market (Hamoudi and Thomas 2014). If either of these latter mechanisms are important, then co-residence with a pensioner could be associated with lower reservation wages, as we find. Overall, the regression results in Table 4 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.

An assumption of our model is a constant arrival rate for job offers which (in combination with the assumption that all other structural parameters are time-invariant) implies that the reservation wage is constant. Because CAPS asks about reservation wages in each wave of the panel, we can test whether an individual's reservation wage is constant or whether it declines with unemployment duration. We do so by regressing the reservation wage on unemployment duration, with individual fixed effects to account for time-invariant heterogeneity. We find no evidence of declining reservation wages. The result is robust to allowing for multiple unemployment spells across the panel, as shown in Table A2. We conclude that the assumption of constant reservation wages is plausible.[15]

Overall, then, our impression of the quality of CAPS survey data on reservation wages is mixed. The evolution of self-reported reservation wages over time and their association with observable characteristics appear to match the assumptions of our model. However, the underlying heterogeneity of reservation wages and the frequency with which they exceed accepted wages are reconciled

[15]This is convenient since the leading methods for incorporating time-varying reservation wages in structurally estimated search models make assumptions that do not fit the South African context: 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 is at odds with the South African experience.

in our model only by measurement error, which is surely an oversimplification. This uneven quality is perhaps unsurprising. Young people with little to no experience in the labor market may have difficulty when asked to reflect on their preferences for accepting employment, particularly in a setting like South Africa where youth unemployment is so high. We nonetheless proceed to use self-reported reservation wages in one version of the model, with a healthy skepticism applied to the results.

Finally, we consider the adequacy of our distributional assumptions used to form the likelihood function. Figure 2 shows kernel density estimates of accepted wages and first unemployment spells, respectively; recall that both distributions are assumed exponential for purposes of estimation.[16] Although the empirical distributions from the full sample may mask considerable heterogeneity and thus cannot show that our distributional assumptions are correct, observable patterns consistent with the exponential distribution (e.g., monotonically decreasing with a long right tail) at least suggest that our estimates may fit the data well. The accepted wage distribution, panel [a], does exhibit the left tail mode and long right tail that is characteristic of the exponential distribution; in our model, measurement error will account for the increasing density in the left tail. The unemployment duration density (for completed spells; panel [b] also exhibits these patterns, and appears to be consistent with our assumption of a constant hazard rate of unemployment exit, in the aggregate.[17]

4 Model Parameter Estimates

In this section, we discuss the parameter estimates of the structural model that we subsequently use to analyze the wage subsidy. Recall the key parameters governing the model are q (the job offer arrival rate), λ (the wage offer), and σ_ϵ (the standard deviation of the measurement error). We incorporate individual heterogeneity by modeling the job arrival rate and the wage offer as log linear functions of a parsimonious set of covariates: indicator variables for female, black, high school

[16]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.

[17]Although the duration 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.

graduate, at least some college, high ability,[18] and previous work experience; the omitted group is low-ability coloured males with less than a high school education and no previous work experience. The measurement error variance is estimated as a single parameter for the entire sample, however.

As noted above, the reservation wage plays a key role in identification of the model. We discuss results using the survey reports of the reservation wage first, because this is the most novel feature of our data, and then discuss results using two alternative approaches.

4.1 Estimates using reservation wage survey reports

As a first approach, we estimate (7) using the median reservation wage within cells defined by the included covariates as our measure of w^*. Results are presented in Table 5, column 1.

Results for q, the job offer arrival rate, are given in the first column. 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.[19] The baseline monthly probability of a job offer is 23%. The reported coefficients on $\ln q$ represent the marginal effect, in log points, on the offer arrival rate. We see that females and blacks face offer arrival rates that are .14 and .48 points (or approximately 14% and 48%) lower than those for males and coloureds, respectively. High school graduation and post-secondary schooling generate large returns on offer arrivals (coefficients of .46 and .26, respectively), although the post-secondary coefficient is not precisely estimated, likely due to the small numbers in this category in the sample. High ability and previous work experience also increase the offer arrival rate considerably (coefficients of .30 and .23, respectively). The estimates imply that a coloured male, low-ability high school dropout with no previous work experience has a monthly offer probability of just 23%, but that high ability, previous work experience and high school education double this probability, to 46%.

Results for λ, the wage offer distribution parameter, whose baseline represents the mean (and standard deviation) of the wage offer distribution are given in the second column. Coefficients are

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

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

marginal effects in log points, as before. The estimated baseline wage offer, at R725, is quite low relative to the mean accepted wage of R2,172.[20] Not surprisingly, the model predicts that only 28% of wage offers are accepted.[21] As with the offer arrival rate, the estimates imply considerable labor market disadvantages for black and female youth (coefficients -.24 and -.20, respectively). Schooling, ability and previous work experience generate large returns, however, with the coefficient of .58 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 coloured male, low-ability high school dropouts with no previous work experience to their high ability, high school-educated and experienced counterparts, we find that the former face a mean wage offer of R725, while the latter receives offers nearly twice as large, at R1,406. The estimated measurement error standard deviation, σ_ϵ, implies that measurement error accounts for 32% of the standard deviation in accepted wages.[22]

4.2 Estimates with Alternative Measures of the Reservation Wage

The base case approach above used within-cell median reported reservation wages as the measure of w^*. Reported reservation wage data, though, are rare. In this section, we estimate the model using two alternative measures of the reservation wage that do not require reported reservation wages. First, we use the fifth percentile of accepted wages (by cell), denoted w_{q_5} as our measure of the reservation wage. We next estimate the model leaving the reservation wage as a parameter to be estimated as described in Section 2.2. We denote this measure as w^*_{MLE}. Estimating the model with these alternative measures of the reservation wage serves two purposes. It allows us to infer the "value-added" of having data on actual reservation wages. Usually, reservation wages have to be inferred (or estimated). By comparing estimates with actual reservation wages to those without, we highlight the role that the reservation wage data play. It also allows us to investigate how the

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

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

[22]Bound and Krueger (1991) found that measurement error accounts for 18% of the variance in reported annual earnings for men in the US.

impact of the wage subsidy varies depending on which measure of the reservation wage is used.

Table 5, columns 2-3 present parameter estimates for each alternative. Column 2 reports results with w_{q_5}, while column 3 reports estimates with w^*_{MLE}. We find that results are qualitatively similar regardless of the measure of the reservation wage used 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 with the actual reservation wage data, w^*, than is the case when we use inferred or estimated reservation wages: a monthly job offer probability of .23, versus .10 and .18 under w_{q_5} and w^*_{MLE}, respectively. Although differences among the models shrink 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 selective about which to accept.

Differences among the models' estimates of λ, the wage offer distribution parameter, are also quite striking. The baseline mean wage offer of R1,070 in the model with w_{q_5} (Table 5, column 2) is 48% greater that of the model with w^*. The baseline offer of R814 in the model with w^*_{MLE} (column 3), while not nearly as high, still exceeds the baseline under w^* by more than 10%. 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: 28% under w^*, versus 61% and 41% under w_{q_5} and w^*_{MLE}, respectively.

Considered in conjunction with the offer arrival 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 youth 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 the expected pattern: black and female youth have lower reservation wages relative to coloured males, consistent with their lower status in the labor market, while reservation wages are increasing in schooling and ability. Interestingly, the negative coefficient on previous work experience suggests that youth 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 self-reported reservation wages begs the question, "If the South African youth labor market is so bad, why are youth turning down so many jobs?" It is unlikely that youth are actually receiving, and refusing, job offers with the frequency implied by our estimates. Instead, the estimates are more likely to represent "implicit refusals" of low-wage offers that are available in principle, but that are not literally made by employers to unemployed youth. The matching costs incurred by both sides may exceed the surplus generated by these low-wage matches.

Comparing results across the various reservation wage measures, another possibility is that the estimates generated by self-reported reservation wages suffer from poor data quality. Given the inconsistencies uncovered in the reservation wage reports that we discussed in Section 3.2, it is possible that the data severely mismeasure an individual's willingness to accept a job. We reserve judgment on the merits of the reservation wage data until considering the evidence on model fit presented in the next section.

4.3 Model Fit

The structural search model generates predictions for the distributions of unemployment durations and accepted wages. Before considering a formal Lagrange Multiplier test, we first offer a more qualitative comparison of the predicted distributions and their empirical counterparts.

We first consider 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 6 shows, in column (1), the empirical survivor function at various monthly durations, along with model estimates depending on how the reservation was is treated in columns (2)-(4). For example, 73 percent of actual unemployment spells exceed 3 months while the model, for each treatment of the reservation wage, predicts that 78 percent of the spells would exceed 3 months. The model almost exactly predicts the fraction of spells exceeding 6 and 12 months, but over-predicts the fraction of spells lasting 24 and 36 months.

We next consider the distribution of accepted wages in Table 7. The model predicts the mean of the accepted wage distribution pretty well. The actual mean is R2,172 while, when we use the reported reservation wages, w^*, the model predicts a mean accepted wage of R2,116. The model, though, underestimates the standard deviation of the distribution of accepted wages, and this is seen by comparing actual and predicted accepted wages at different parts of the distribution. The empirical distribution has a longer right tail than that predicted by the model, and this explains the differences in the mean and standard deviation reported in the top two rows of the table.

We conclude from our qualitative evaluation of model fit that the model does fairly well for most of the mass of the distributions but does less well in the right tails. That is, the model does not fit the really long unemployment durations or really high accepted wages very well. At some level, this is unsurprising. The model is quite simple and it is asking a lot to fit the far right tail of the distributions of unemployment duration and accepted wages.

We test the model more formally by conducting Lagrange Multiplier (LM) tests.[23] This test essentially asks whether moments of the distributions predicted by model match their empirical counterparts. The LM test is similar in spirit to the Kolmogorov-Smirnov test—a nonparametric test for the equality of two distributions. Results are given in the bottom panels of Tables 6 and 7. We consistently reject the null hypothesis that the model is correctly specified. This too is unsurprising given the simplicity of the model and the high bar set by a test that is, in essence,

[23] Appendix C describes details of these tests.

comparing entire distributions of outcomes.

On balance, none of the three reservation wage measures considered produces estimates that are clearly superior based on model fit. However, the strikingly low offer acceptance rate and high measurement error found in the model using reservation wage reports casts doubt on the validity of this measure, as does the high proportion of youth reporting a reservation wage greater than their accepted wage. The more reasonable offer acceptance rate and measurement error found in the model using the 5th percentile accepted wage lead us to prefer this measure among the three. Nonetheless, the reservation wage self reports are novel, particularly for a developing country. We will therefore report results of our wage subsidy simulation under all three measures, as well as a series of additional robustness checks of the model in the next subsection.

4.4 Robustness checks

Given the different parameter estimates found using alternative measurements for the reservation wage, it is useful to explore further the robustness of our model using different reservation wage measures and samples. Table A3 presents results from a series of such exercises. Column 1 presents results using individual reservation wage reports, w_i^*, rather than their median within covariate cell. Although coefficients are similar to those using the median reservation wage report, the measurement error required to reconcile the reservation and accepted wage distributions balloons to 101% of the observed wage distribution (the amount may exceed 100% because we compare the parameter of an estimated distribution to an empirical distribution). This finding reflects the wide variation present in the reservation wage reports, which becomes more muted when using the median report.

Columns 2 and 3 use the 10th and 20th percentile of accepted wages within covariate cell as the reservation wage. Comparing these results with those using the 5th percentile accepted wage (Table 5, column 2), we find that the estimated baseline offer arrival and acceptance rates increase, the mean wage offer decreases, and the wage measurement error increases in the wage percentile used as the reservation wage. For the 20th percentile accepted wage, results are quite similar to those using the median reservation wage report (Table 5, column 1). This highlights the relatively high reservation wages reported in the sample; only by reducing the implied reservation wage to the 5th percentile do we arrive at more reasonable estimates.

Because the youth labor market might be strongly segmented by race in South Africa, in columns 4-5 of Table A3 we estimate the model separately for black and coloured youth, using our preferred reservation wage measure w_{q_5}. Interestingly, for offer arrivals we find higher returns to schooling and previous experience for black than coloured youth, but lower returns to ability. For wage offers the opposite is true: black youth have lower returns to schooling, higher returns to ability, and lower returns to previous experience. These results are consistent with a youth labor market in which blacks must show more concrete signals of productivity (such as schooling and experience) than coloureds, but find it more difficult to signal their ability to prospective employers. Once hired, however, schooling and experience matter more for coloured youth in securing higher wages. Because of these differences, we explore the effects of the employer wage subsidy for each race separately, as well as for the full sample.

Finally, in column 6 we report results when including students and those who have been out of school for less than a year in the sample. For students, an unemployment duration begins in the first calendar month in which work or job search is reported; students who never report working or searching or have a left-censored spell remain excluded. Definitions of all other variables remain unchanged. Using this augmented sample, we obtain results that are very similar to those from the full sample. The offer acceptance probability and measurement error as a proportion of the observed wage standard deviation are nearly unchanged relative to the main results.

5 Analysis of a Youth Wage Subsidy

5.1 The impacts of a wage subsidy

Having estimated a structural search model consistent with the observed distributions of unemployment and accepted wages, we now use this model to prospectively analyze the impact of a wage subsidy to youth in the Cape Town area.

After several years of debate, the South African government enacted a youth wage subsidy in

2014. Youth aged 18-29 are eligible, and may receive the subsidy for up to two years. In the first year, the policy would subsidize 50 percent of wages up to R2,000 per month; provide a subsidy of R1,000 for those earning between R2,001-4,000 per month; and taper the subsidy to zero at a rate of 50% per additional rand of earnings between R4,001-6,000 per month. The subsidy is halved in the second year of employment (Republic of South Africa 2013). Its range is therefore 0-1,000 rand per month.

The impact of a wage subsidy will depend on its level, of course, but also on how individuals respond to the subsidy. Intuitively, the subsidy shifts the wage offer distribution to the right and the bigger the subsidy, the bigger the shift. Knowing that expected wage offers will be higher, individuals increase their reservation wages (see eq. (3)). In the new equilibrium, the probability of accepting a job offer increases as does the mean accepted wage. Correspondingly, unemployment spells are shortened. The *magnitude* of these responses, though, is an empirical question.

We model the wage subsidy as a shift right in the wage offer distribution by the full amount of the subsidy, s. Hence the entire distribution, including the truncation point, shifts by s. This approach implicitly assumes that the subsidy is fully passed through to job seekers in the form of wage offers. In this sense, this is a best-case scenario for the impact of the subsidy, since to the extent that employers have some market power in the youth labor market, pass-through will not be complete.[24]

The first step of simulating the impact of a wage subsidy is to compute the new reservation wage. In our 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 individuals' reported reservation wages as in our analysis, we must update w^* by calibrating some elements of θ that we did not observe (or estimate) in our baseline specification. We update w^* in a fashion that is consistent with our search model, as

[24]Note that the way we model the subsidy does not exactly match the policy, under which 50% of the accepted wage (up to R2,000) would be subsidized. Under our assumption of exponential wage offers, modeling the subsidy as a proportion of the offered or accepted wage would require altering both the mean and variance of the wage offer distribution. We prefer instead to focus only on altering the location but not the shape of the distribution.

expressed in (3). Specifically, we use our maximum likelihood estimates of (λ, q) and calibrate the model parameters not estimated by our model (b,δ,p) such that they reproduce the value of w^* used in the baseline (no subsidy) estimation. We calibrate p according to observed job separations in the data; choose $\delta = .95$ annually; and then choose b to match w^* to the data (by inverting the reservation wage function). We then update w^* by varying the subsidy value s, holding all other parameters fixed.

Results of this exercise are given in the top panel of Figure 3. That panel shows the new reservation wage and how it varies depending on the level of the subsidy.[25] The subsidy $s = 0$ corresponds to the estimates discussed in the preceding sections, and s increases to R1,000 (the maximum allowable under the recently enacted policy) in increments of 100 along the horizontal axis. The top panel shows that the reservation wage increases monotonically with the subsidy and that the relationship is close to linear. In the preferred specification using the model with the 5th percentile accepted wage, a R1,000 subsidy increases the reservation wage by about R596 and, while the level of the reservation wage depends on how it is estimated, the response of the reservation wage to a subsidy is about the same for each treatment of the reservation wage.

The higher reservation wages that result from the introduction of the wage subsidy result in higher accepted wages. The bottom panel of Figure 3 displays these results. Again, the relationship between the mean accepted wage and the subsidy is about linear and that relationship is fairly invariant to the way that reservation wages are treated in the estimation. A R1,000 subsidy increases the mean accepted wage by about R571 (and recall this is assuming that the subsidy is fully passed through to the wage offer distribution).[26] Hence, only about 57% of the wage subsidy shows up as an increase in the mean accepted wage. Of course, the wage subsidy also impacts the length of unemployment spells so the 57% figure is not the end of the story.

The rise in the reservation wage is one measure of the subsidy's impact. The subsidy also raises the likelihood that an individual will accept a job offer. This is illustrated in Figure 4. When we model reservation wages using the 5th percentile of accepted wages, w_{q_5} (as opposed to

[25]In Figures 3-5, the lines labeled `wrhat=wr` correspond to the model estimated with w^*; `wrhat=wp5` to w_{q_5}; and `wrhat=wrmle` to w^*_{MLE}.

[26]The reservation wage and mean accepted wage increase by the same amount because the entire accepted wage distribution has shifted to the right by the increase in the reservation wage.

w^* or w^*_{MLE}), the probability of accepting a job offer increases from .61 to .84 with a subsidy of R1,000. This translates into shorter unemployment spells–presumably the foremost goal of the wage subsidy–and this is shown in Figure 5. Focusing again on the results that use the 5th percentile accepted wage, w_{q_5}, the fraction of youth who report an unemployment spell of 12 months falls from 45% with no subsidy to about 33% with a R1,000 subsidy. A 12 point reduction in long term unemployment strikes us as quite sizeable. The reduction is of similar magnitude (14 percentage points) when we estimate the model using reservation wages estimated directly by maximum likelihood. These percentage point declines carry over to comparable declines in the probability of 24 month unemployment spells, as shown in the bottom panel of Figure 5. The model using w_{q_5} has 25% of individuals reporting a 24 month period of unemployment, and this falls to about 13% with a R1,000 wage subsidy.

Because of the parameter differences we found when estimating the model separately by race in Table A3, we also simulated the wage subsidy separately for black and coloured youth using these parameters. The results, shown in Figure 6, reveal that the subsidy is effective at increasing wages and reducing lengthy unemployment spells for both groups. Differences emerge in the magnitudes of the subsidy's effect, however. For blacks, the R1,000 subsidy would increase mean wages from R1,621 to R2,002, an increase of 24%. For coloureds, the increase would be from R2,285 to R2,964, or 30%. For blacks, the probability of experiencing an unemployment spell of at least 12 months would fall from 63% to 43%, or a decrease of 32%, while for coloureds the decrease would be from 36% to to 27%, or a 25% decrease. The subsidy would therefore be relatively more effective at giving blacks a "foot in the door" of the labor market by curbing their unemployment, while it would give a greater boost to the wages of coloured youth.

Overall, our prospective analysis of an employer wage subsidy indicates that the subsidy will be effective in reducing unemployment spells, even in a model that generates substantial unemployment in the absence of such a subsidy. The avenues through which the subsidy works are more subtle than would be the case in an "Econ 101" model of supply and demand. We find that the subsidy raises reservation wages and so, even with an assumed 100% pass-through of the subsidy as it impacts the wage offer distribution, accepted wages only rise by about 57% of the subsidy. This amount of pass-through, though, is enough to generate substantial declines in long term unemployment spells. The fact that all of the impacts of the subsidy illustrated in Figures 3 - 5 are almost linear suggests that the level of the wage subsidy is mostly a political decision. That is, there are no obvious inflection points that would support an argument for a subsidy set at a particular level.

5.2 Caveats

Figure 5 represents our estimate of the impact of a wage subsidy on unemployment spells, but the model that generates these results is necessarily much simpler than the youth labor market in metro Cape Town. There are assumptions in both the underlying search model as well as in how we model the wage subsidy that merit highlighting.

Notably, the partial equilibrium nature of our search model treats labor demand as exogenously determined and fully described by the Poisson job offer arrival rate and wage offer distribution. Our model may fail to capture additional idiosyncratic frictions in the South African labor market that firms and workers face, such as firing restrictions and the lack of a vibrant informal sector. Moreover, young people may not behave entirely according to the reservation wage policy described by our simple search model, as the large proportion who accept wages below their stated reservation wage suggests. The wage subsidy we model may not pass through completely to the wage offer distribution, as we assume, if firms can exercise market power and capture rents from the subsidy.

Finally, we ignore any possible general equilibrium effects from the wage subsidy: even if targeted only to the young, youth make up a disproportionate share of South Africa's unemployed, as noted in the Introduction. An influx of newly employed youth due to the subsidy could exert some downward pressure on the wages of those already employed. The extent of this effect would depend on the substitutability among workers, and the extent to which institutional rigidities segment sectors of the labor market. Moreover, the increased purchasing power of youth employed due to the subsidy could stimulate consumer demand, driving up labor demand with it. These potential spillover effects of the wage subsidy are beyond the scope of this paper.

Nonetheless, we believe that our analysis adds to the existing literature and political conversation about wage subsidies by considering how the subsidy would affect the reservation wages of job seekers in an environment of equilibrium unemployment. Our analysis of the effects of a wage subsidy complements those of Pauw and Edwards (2006), Burns et al. (2010) and Go et al. (2010), who consider wage subsidies in the context of computable general equilibrium (CGE) models of the South African economy and find positive effects on employment, wages and GDP.

While not directly comparable, Levinsohn et al. (2013) discuss the results of a randomized control trial they conducted. The RCT did not include Cape Town and only included Africans (but no Coloureds), but the wage subsidy was R833 per month (or half the wage, whichever was smaller) and so is not far off from the R1,000 subsidy discussed above. They found that the subsidy increased employment among the 20-24 year olds in the sample by about 25 percent (or 7.5 percentage points.)

6 Conclusion

Persistently high youth unemployment is one of the most pressing problems in South Africa. The South African government has enacted an employer wage subsidy to address the issue. Because the policy has only been in effect since January 1, 2014, it is too early to conduct an observational study of its impact. Instead, we prospectively analyze such a policy. Recognizing that a credible estimate of the policy's impact requires a model of the labor market that itself generates high unemployment in equilibrium, we estimate a structural search model that incorporates both observed heterogeneity and measurement error in wages. We find that the estimated model replicates the observed unemployment spells and the distribution of accepted wages reasonably well, although not perfectly. Using the model to examine the impact of a wage subsidy, we find beneficial effects for youth even after accounting for how the subsidy increases reservation wages. We find that a R1,000/month wage subsidy paid to employers leads to more frequent job offer acceptances, increased accepted wages and substantial declines in even long term unemployment. In addition to these economic benefits, the wage subsidy could also increase social cohesion by reducing South Africa's staggeringly high youth unemployment.

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A Derivation of Likelihood Function

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:

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

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

An implication of this form of the wage distribution is that the accepted wage distribution will be truncated at $w^* = \bar{w_o} - \lambda$, where $\bar{w_o}$ is the mean observed wage. We use this restriction in the version of the model that estimates the reservation wage directly.

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 Definitions

The sample is all black and coloured young adults in CAPS who began as enrolled students at the inception of the monthly calendar data (August 2002) but have exited school; are observed for at least 12 months since leaving school in the monthly 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. 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 the 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 in the calendar data prior to school exit. Full-time work is defined as an an average of at least 35 hours per month.

Survey weights are applied to all analysis. The survey weight is the young adult sample weight, which is adjusted for the sample design plus household and young adult non-response at in Wave 1, and serves to make the sample representative of the population of Cape Town youth.

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.[27] 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).[28]

[27] 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.

[28] 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: Sample selection and attrition

Panel A: sample selection rules	N
Full sample	4,752
whites	596
left-censored	1,558
students	813
out of school < 1 year	395
missing reservation wage	51
wage outlier	18
Final sample	1,321
Panel B: reasons for attrition	
complete spell	943
incomplete spell:	
still unemployed	317
moved	28
dead	2
unspecified	31

Panel A shows full and final sample size in first and final row, respectively, after sample selection rules applied. Counts of observations dropped due to successive application of each restriction reported in middle rows. "Left-censored" are those never observed in school in monthly calendar data. "Students" are those who have not left school for at least 3 consecutive months in monthly calendar. "Wage outliers" are those reporting accepting wages less than first percentile or greater than 99th percentile in sample. Panel B shows numbers of complete and incomplete first unemployment spells since school exit, with reasons for incomplete spells among those with right-censored spells.

Table 2: Summary statistics

Variable	N	Mean	Std. Dev.
female	1,321	0.53	0.50
black	1,321	0.30	0.46
coloured	1,321	0.70	0.46
age	1,321	19.4	2.1
schooling	1,321	10.6	2.1
ability score	1,321	0.04	0.86
wage	900	2,172	1,514
reservation wage	1,321	1,464	1,715
(reservation wage > wage)	900	0.26	0.44
first UE spell	1,321	12.3	11.1
UE spell≥1yr	1,321	0.45	0.50
censor	1,321	0.25	0.43
previously worked	1,321	0.29	0.45
full-time	943	0.77	0.42
never searched	1,321	0.35	0.48
return to school (full-time)	1,321	0.00	0.00
return to school	1,321	0.05	0.23

Sample is black and coloured youth 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. Never searched excludes those who obtain employment immediately after school exit. Survey weights applied.

Table 3: Unemployment duration, by observable characteristics

	First UE spell (mean duration, months)	Fraction with 1st UE spell $\geq$ **1** year	Fraction with 1st UE spell $\geq$ **2** years	Fraction unemployed after 12 months	Fraction right-censored
male	10.6	0.38	0.22	0.50	0.20
female	13.7	0.52	0.35	0.59	0.30
black	17.2	0.66	0.52	0.72	0.37
coloured	10.2	0.37	0.20	0.48	0.20
age:					
$\leq$18	14.3	0.52	0.35	0.60	0.34
19-22	11.5	0.43	0.25	0.54	0.21
$\geq$23	8.3	0.31	0.19	0.37	0.14
schooling:					
$\leq$9	16.6	0.61	0.43	0.72	0.38
10 or 11	12.9	0.50	0.29	0.57	0.28
12	9.4	0.33	0.17	0.44	0.15
>12	6.6	0.22	0.23	0.37	0.12
low ability	14.6	0.55	0.36	0.64	0.31
high ability	9.5	0.33	0.20	0.44	0.18
never worked before	15.0	0.6	0.3	0.6	0.30
previously worked	5.4	0.18	0.12	0.32	0.12
some search	10.7	0.38	0.26	0.50	0.18
never searched	15.2	0.59	0.35	0.65	0.38

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 unemployment 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. Survey weights applied.

Table 4: Regressions of self-reported reservation wage on observable characteristics

	(1)	(2)
female	-88.1	-76.6
	(106.4)	(113.4)
black	-258.2	-362.8
	(96.3)***	(136.7)***
age	-110.3	-167.5
	(202.4)	(240.4)
age^2	4.1	6.3
	(5.2)	(6.3)
schooling	80.6	83.9
	(36.7)**	(41.5)**
ability score	264.3	257.0
	(73.9)***	(80.7)***
pensioner in HH		-241.6
		(106.6)**
father employed		-36.6
		(122.2)
ill		-62.1
		(128.0)
parents want youth to work		-56.6
		(28.0)**
co-resident with parent		171.8
		(79.2)**
own child in HH		-169.1
		(155.2)
N	1,321	1,098
R^2	0.06	0.08

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. Survey weights applied.

Table 5: Parameter estimates under alternative reservation wage measures

Reservation wage	(1) w^*	(2) w_{q5}	(3) w^*_{MLE}
$\ln q$ (offer arrival rate): baseline	0.23	0.10	0.18
constant	-1.49	-2.26	-1.74
	(0.17)	(0.10)	(0.20)
female	-0.14	-0.48	-0.31
	(0.17)	(0.11)	(0.18)
black	-0.48	-0.51	-0.50
	(0.18)	(0.09)	(0.19)
HS grad	0.46	0.47	0.33
	(0.18)	(0.11)	(0.18)
at least some college	0.26	0.75	0.40
	(0.26)	(0.24)	(0.27)
high ability	0.30	0.11	0.08
	(0.17)	(0.10)	(0.19)
previous work	0.23	0.75	0.41
	(0.16)	(0.13)	(0.17)
$\ln \lambda$ (wage offer parameter): baseline	725.2	1069.9	814.5
constant	6.59	6.98	6.70
	(0.10)	(0.07)	(0.11)
female	-0.20	-0.09	-0.17
	(0.09)	(0.06)	(0.09)
black	-0.24	-0.22	-0.22
	(0.11)	(0.07)	(0.11)
HS grad	0.24	0.21	0.28
	(0.10)	(0.07)	(0.10)
at least some college	0.80	0.58	0.76
	(0.14)	(0.12)	(0.14)
high ability	0.12	0.21	0.20
	(0.10)	(0.08)	(0.11)
previous work	0.58	0.41	0.57
	(0.10)	(0.07)	(0.10)
$\ln \sigma_\epsilon$ (measurement error s.d.): baseline	487.8	247.5	349.0
constant	6.19	5.51	5.85
	(0.05)	(0.11)	(0.07)
$\ln w^*$: baseline			926.81
constant			6.83
			(0.08)
female			-0.09
			(0.07)
black			-0.21
			(0.07)
HS grad			0.16
			(0.07)
college			0.37
			(0.14)
high ability			0.08
			(0.08)
previous work			-0.12
			(0.09)
N	1,321	1,321	1,321
$\ln L$	-919,453	-20,694	-16,690
$\Pr(w \geq w^*)$	0.28	0.61	0.41
σ_ϵ (measurement error s.d.) as proportion of observed wage s.d.	0.32	0.16	0.23

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. "Baseline" refers to value of exponentiated constant term for each parameter, and may be interpreted as parameter level for left-out category (coloured 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., $\Pr(w \geq w^*) = \int \Pr(w \geq w^*|x) f(x) dx$. Survey weights applied.

Table 6: Empirical and predicted unemployment survivor functions

	$\mathbf{Pr}(d \geq d_0)$			
	(1)	(2)	(3)	(4)
	empirical	w^*	w_{q_5}	w^*_{MLE}
UE duration (months)				
3	0.73	0.78	0.78	0.78
6	0.62	0.63	0.64	0.63
12	0.45	0.44	0.45	0.44
24	0.16	0.24	0.25	0.24
36	0.03	0.15	0.15	0.15
χ^2		361.6	376.6	365.6
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 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, p. 261-2). Appendix C describes this test in greater detail.

Table 7: Moments and quantiles of empirical and predicted accepted wage distributions

	Accepted wage			
	(1)	(2)	(3)	(4)
	empirical	w^*	w_{q_5}	w^*_{MLE}
mean	2172.0	2116.8	2094.9	2080.6
std. dev.	1514.4	1203.2	1545.5	1368.2
quantiles				
0.1	855.8	846.4	652.5	821.0
0.25	1224.6	1266.6	1000.7	1166.7
0.5	1719.1	1835.2	1604.8	1670.0
0.75	2617.6	2609.8	2633.8	2477.5
0.9	4064.4	3715.4	4168.5	3767.9
χ^2		209.7	202.7	192.8
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 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, p. 261-2). Appendix C describes this test in greater detail.

Table A1: Comparison of CAPS and national youth

Variable	CAPS	Census (Cape Town)	Census (national)
female	0.53	0.52	0.51
black	0.30	0.42	0.91
coloured	0.70	0.58	0.09
age	17.4	18.1	17.9
schooling	10.6	10.2	10.0
employed	0.43	0.36	0.22
wage	2,172	2,311	1,727
full-time	0.77	0.87	0.89

Table shows means by sample. Census sample is youth 14-22 in 2001 (10% sample) for female, black, coloured, age, and full-time; youth age 18-26 in 2007 (2% sample) for remaining variables. "Employed" is employment in month 12 since leaving school for CAPS and broad definition for LFS. Wage is monthly full-time equivalent in real South African rand, base August 2002 (wage not adjusted for FTE in Census because work hours not available for 2007). Full-time work is work of at least 35 hours/week on average. Wage and full-time conditional on employment and non-enrollment. Survey weights applied.

Table A2: Regressions of self-reported reservation wage on unemployment duration

	(1)	(2)
unemployment duration	111.2	3.2
	(122.6)	(17.1)
Observations	1,701	2,143
R-squared	0.75	0.68
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. Table shows regression of reservation wage on unemployment duration, with both variables measured at the time of interview. Reservation wage measured in (real) rand per month; unemployment duration in months. All regressions include individual and wave fixed effects. Regressions including multiple spells include fixed effects for spell number within panel. Survey weights applied.

Table A3: Robustness to alternate reservation wage measures and samples

sample	**full**	**full**	**full**	**black**	**coloured**	**inc. students**
reservation wage	$\boldsymbol{w_i^*}$	$\boldsymbol{w_{q_{10}}}$	$\boldsymbol{w_{q_{20}}}$	$\boldsymbol{w_{q_5}}$	$\boldsymbol{w_{q_5}}$	$\boldsymbol{w_{q_5}}$
	(1)	(2)	(3)	(4)	(5)	(6)
ln $\boldsymbol{q}$ (offer arrival rate): baseline	0.15	0.15	0.25	0.06	0.10	0.11
constant	-1.90	-1.87	-1.37	-2.85	-2.31	-2.24
	(0.12)	(0.12)	(0.17)	(0.11)	(0.12)	(0.10)
female	-0.43	-0.43	-0.56	-0.38	-0.35	-0.36
	(0.11)	(0.12)	(0.16)	(0.12)	(0.14)	(0.10)
black	-0.58	-0.66	-0.65			-0.44
	(0.11)	(0.11)	(0.16)			(0.10)
HS grad	0.55	0.43	0.40	0.60	0.34	0.49
	(0.12)	(0.12)	(0.16)	(0.14)	(0.14)	(0.11)
at least some college	0.78	0.54	0.34	0.79	0.60	0.71
	(0.22)	(0.24)	(0.27)	(0.30)	(0.29)	(0.17)
high ability	0.13	0.08	0.16	-0.27	0.44	-0.02
	(0.12)	(0.12)	(0.17)	(0.17)	(0.13)	(0.11)
previous work	0.78	0.68	0.60	1.30	0.61	1.02
	(0.13)	(0.14)	(0.17)	(0.24)	(0.15)	(0.11)
ln $\boldsymbol{\lambda}$ (wage offer parameter): baseline	1061.8	864.0	710.4	924.7	1075.7	1039.4
constant	6.97	6.76	6.57	6.83	6.98	6.95
	(0.09)	(0.08)	(0.10)	(0.08)	(0.08)	(0.07)
female	-0.06	-0.11	-0.06	-0.18	-0.14	-0.13
	(0.09)	(0.08)	(0.09)	(0.10)	(0.08)	(0.06)
black	-0.07	-0.14	-0.17			-0.25
	(0.09)	(0.09)	(0.10)			(0.07)
HS grad	0.12	0.23	0.25	0.09	0.30	0.21
	(0.09)	(0.08)	(0.10)	(0.11)	(0.09)	(0.07)
at least some college	0.34	0.71	0.81	0.58	0.68	0.28
	(0.16)	(0.13)	(0.15)	(0.21)	(0.13)	(0.10)
high ability	0.25	0.20	0.14	0.44	0.00	0.22
	(0.10)	(0.09)	(0.10)	(0.14)	(0.09)	(0.07)
previous work	0.33	0.43	0.46	0.19	0.48	0.33
	(0.10)	(0.08)	(0.10)	(0.13)	(0.09)	(0.07)
ln $\boldsymbol{\sigma_\epsilon}$ (measurement error s.d.): baseline	1527.9	341.8	492.7	191.4	304.1	263.8
constant	7.33	5.83	6.20	5.25	5.72	5.58
	(0.12)	(0.07)	(0.06)	(0.17)	(0.09)	(0.08)
N	1,321	1,321	1,321	613	708	1,932
$\ln L$	-73,113	-17,699	-21,671	-35,078	-83,496	-189,421
$\Pr(w \geq w^*)$	0.36	0.46	0.28	0.62	0.57	0.60
σ_ϵ (measurement error s.d.)	1.01	0.23	0.33	0.17	0.19	0.17
as proportion of observed wage s.d.						

Robust standard errors in parentheses. Reservation wages at top row refer to inputs of maximum likelihood estimation: w_i^* is individual reservation wage from survey; w_{q_p} is pth percentile reservation wage. Sample restricted to black or coloured only where indicated. Sample includes students and those out of school less than one year in final column. For sample including students, those who do not leave school in sample have unemployment duration based on first month in which work or search while in school reported. Students with left-censored spells dropped from sample. Estimation is by maximum likelihood, with starting values taken from converged estimates of sequential estimation of wage offer and unemployment duration distributions. "Baseline" refers to value of exponentiated constant term for each parameter, and may be interpreted as parameter level for left-out category (coloured 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., $\Pr(w \geq w^*) = \int \Pr(w \geq w^*|x)f(x)dx$. Survey weights applied.

Table A4: Reservation wages, by covariate cell

gender	race	schooling	ability	previous work	N	mean	s.d.	p25	median	p75
full sample					1,321	1,464	1,715	780	1,170	1,755
male	coloured	less than HS	low	no	67	1,393	850	813	1,223	1,798
male	coloured	less than HS	low	yes	42	1,402	1,741	594	990	1,462
male	coloured	less than HS	high	no	44	1,262	814	780	1,000	1,713
male	coloured	less than HS	high	yes	35	1,540	1,552	780	1,317	1,525
male	coloured	HS grad	low	no	13	1,593	674	1,458	1,500	1,950
male	coloured	HS grad	low	yes	2	781	2	780	780	783
male	coloured	HS grad	high	no	42	2,426	2,058	1,352	1,884	2,915
male	coloured	HS grad	high	yes	47	1,901	904	1,287	1,943	2,437
male	coloured	some college	low	no	1	341	.	341	341	341
male	coloured	some college	low	yes	5	2,083	1,372	1,460	1,485	1,523
male	coloured	some college	high	no	3	1,733	222	1,461	1,884	1,884
male	coloured	some college	high	yes	11	1,833	1,164	990	1,881	1,950
male	black	less than HS	low	no	140	1,064	783	774	860	1,227
male	black	less than HS	low	yes	10	881	493	487	818	975
male	black	less than HS	high	no	26	1,070	587	786	818	1,462
male	black	less than HS	high	yes	3	999	481	800	800	1,188
male	black	HS grad	low	no	50	1,377	1,149	813	992	1,355
male	black	HS grad	low	yes	9	1,163	564	813	990	1,805
male	black	HS grad	high	no	30	1,532	914	975	1,357	1,884
male	black	HS grad	high	yes	6	1,489	1,145	800	877	1,835
male	black	some college	low	no	1	1,361	.	1,361	1,361	1,361
male	black	some college	low	yes	0	-	-	-	-	-
male	black	some college	high	no	3	3,787	1,990	1,950	3,639	6,017
male	black	some college	high	yes	1	495	.	495	495	495
female	coloured	less than HS	low	no	124	1,089	714	594	942	1,462
female	coloured	less than HS	low	yes	25	1,009	701	390	942	1,458
female	coloured	less than HS	high	no	55	1,800	2,345	792	1,413	1,750
female	coloured	less than HS	high	yes	28	1,268	901	786	975	1,462
female	coloured	HS grad	low	no	33	1,271	880	585	1,040	1,733
female	coloured	HS grad	low	yes	14	1,332	1,968	583	783	975
female	coloured	HS grad	high	no	49	1,806	1,697	975	1,462	2,274
female	coloured	HS grad	high	yes	40	1,542	1,072	975	1,386	1,555
female	coloured	some college	low	no	1	2,799	.	2,799	2,799	2,799
female	coloured	some college	low	yes	3	2,423	2,254	486	1,129	4,531
female	coloured	some college	high	no	7	5,495	12,484	487	990	1,812
female	coloured	some college	high	yes	17	2,190	1,825	1,352	1,683	2,475
female	black	less than HS	low	no	170	986	614	771	793	1,174
female	black	less than HS	low	yes	14	913	369	780	877	975
female	black	less than HS	high	no	34	1,186	817	755	947	1,733
female	black	less than HS	high	yes	1	1,298	.	1,298	1,298	1,298
female	black	HS grad	low	no	61	1,169	745	774	903	1,361
female	black	HS grad	low	yes	6	1,420	927	814	815	1,980
female	black	HS grad	high	no	23	1,390	939	788	1,287	1,560
female	black	HS grad	high	yes	5	5,264	8,275	947	975	1,980
female	black	some college	low	no	8	1,312	512	818	1,127	1,835
female	black	some college	low	yes	2	1,046	340	815	815	1,297
female	black	some college	high	no	10	1,877	882	1,297	1,473	2,729
female	black	some college	high	yes	0	-	-	-	-	-

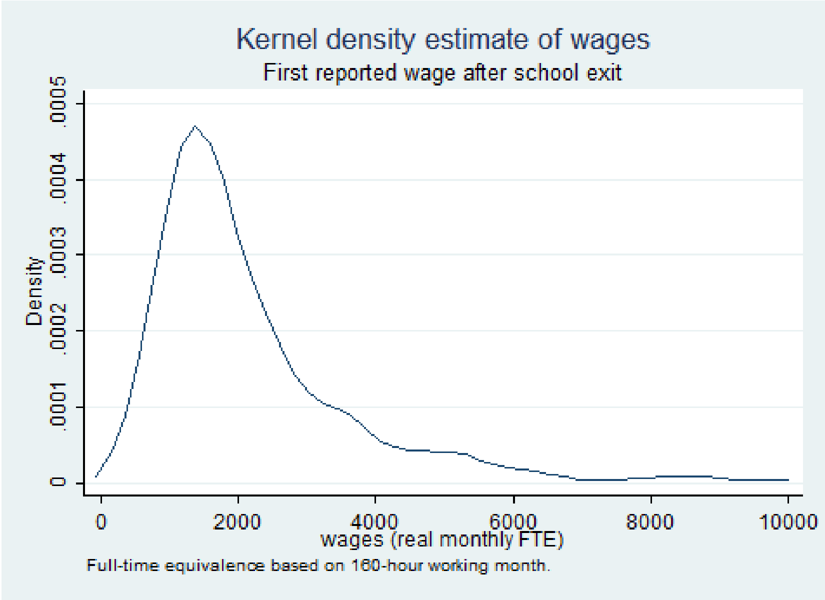
Table shows summary statistics for reservation wage by covariate cell. Reservation wage is last reported reservation wage before first completed unemployment spell or censoring. p[25/75] refers to 25th and 75th percentile, respectively. Survey weights applied.

Figure 1: Wages and reservation wages

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

Figure 2: Density of accepted wages and first unemployment spell

(a)



(b)

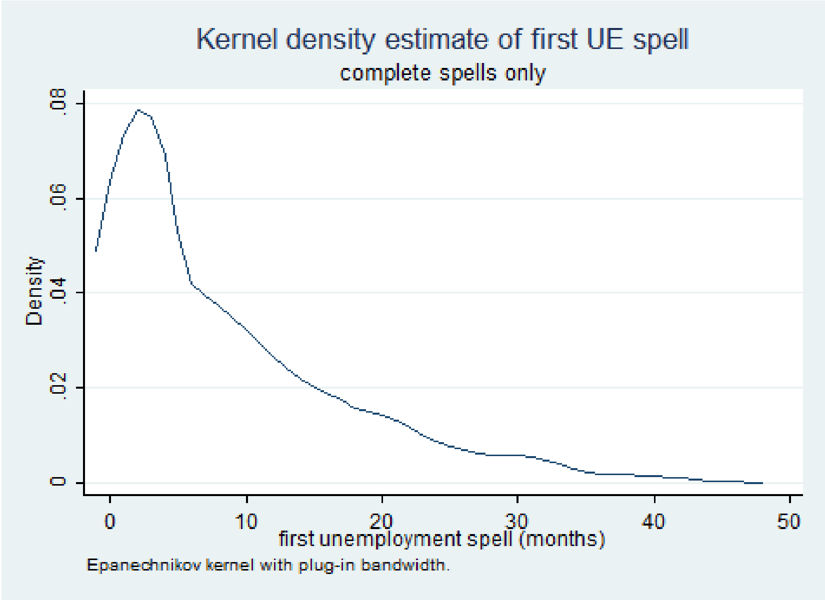
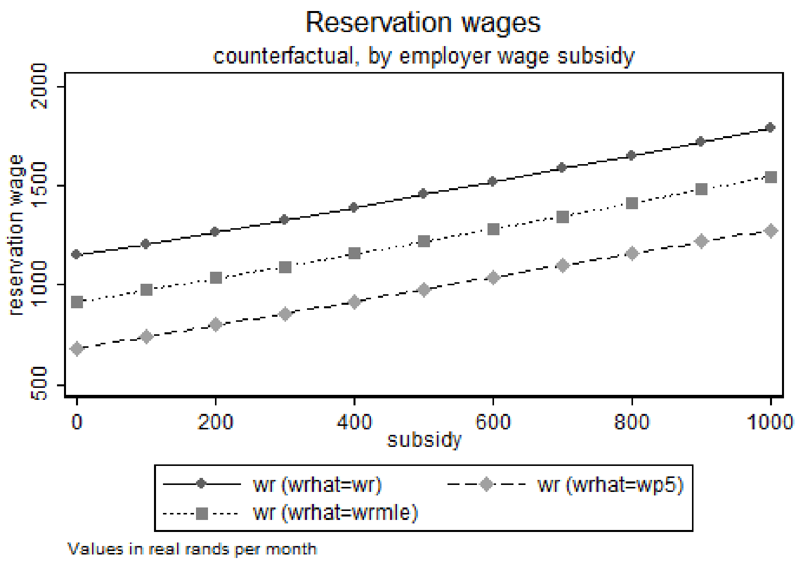


Figure 3: Reservation wages and accepted wages under employer wage subsidy

(a)



(b)

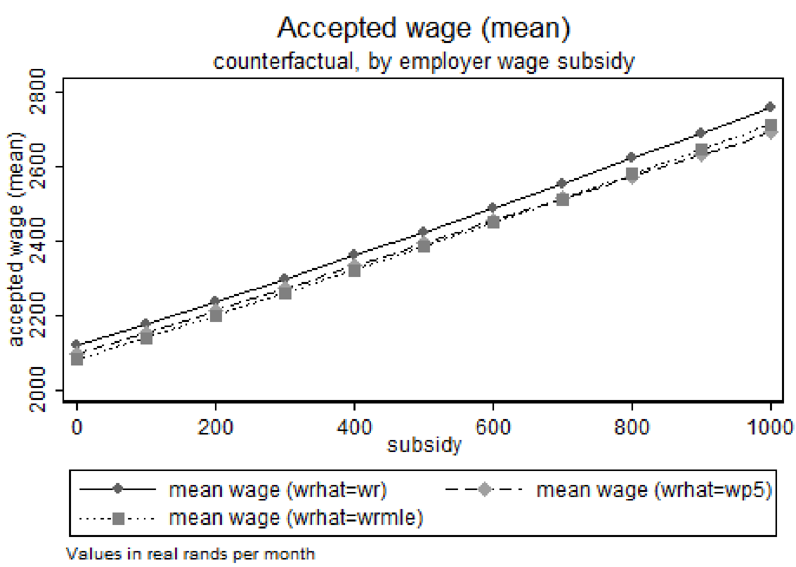


Figure 4: Probability of offer acceptance under employer wage subsidy

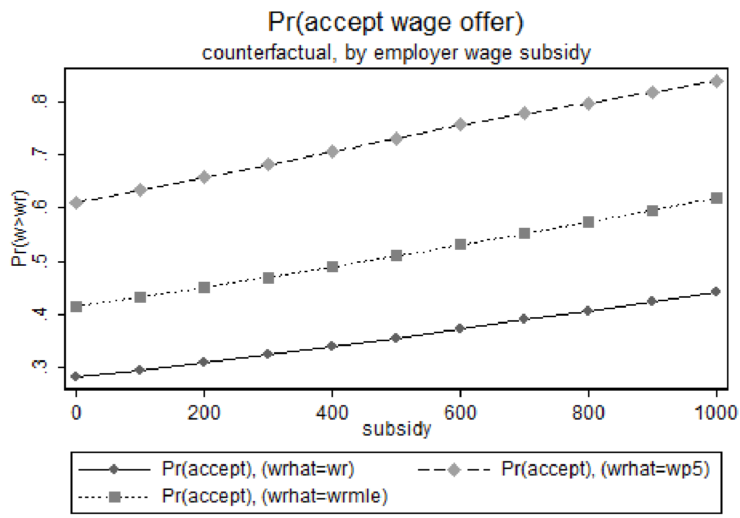
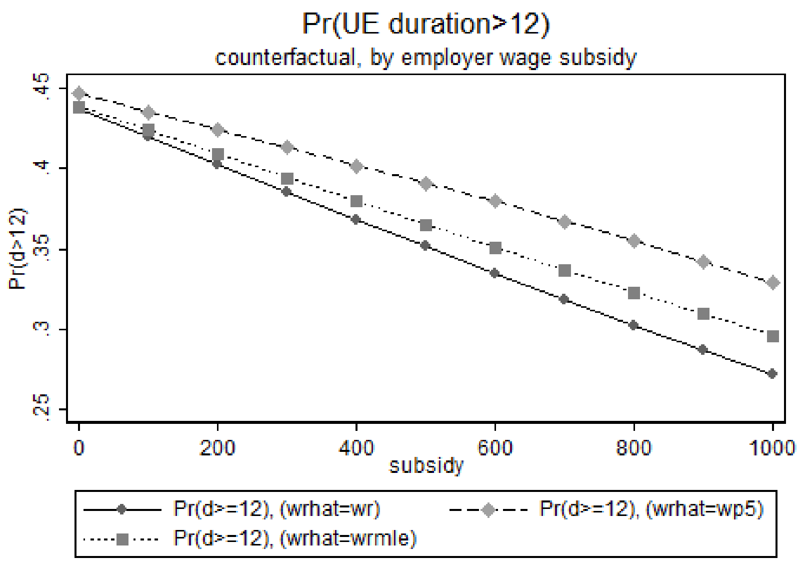


Figure 5: Unemployment survivor function under employer wage subsidy: 12 and 24-month UE spell

(a)



(b)

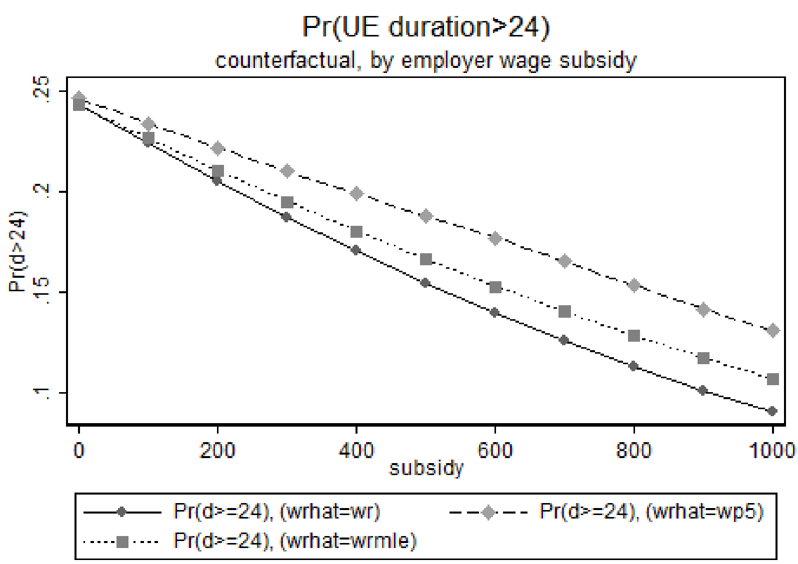
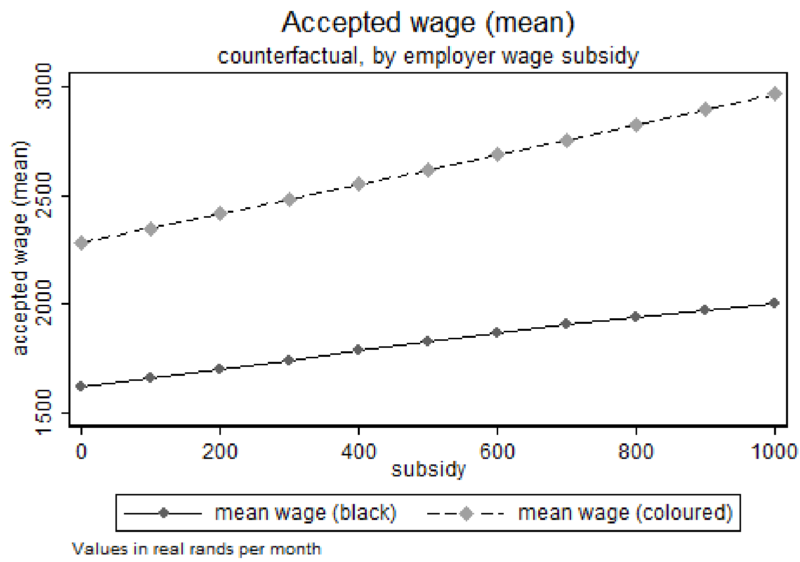


Figure 6: Impact of wage subsidy by race

(a)



(b)